# Designing and Implementing a Human-Robot Team for Social Interactions

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***Abstract*—This study provides an in-depth analysis and practical solution to the problem of designing and implementing a human-robot team for simple conversational interactions. Models for operation timing, customer satisfaction and customer-robot interaction are presented, based on which a simulation tool is developed to estimate fan-out and robot team performance. Techniques for managing interaction flow and operator task assignment are introduced. In simulation, the effectiveness of different techniques and factors related to team performance are studied. A case study on deploying multiple robots in a shopping mall is then presented to demonstrate the usefulness of our study in helping the design and implementation of social robots in real-world settings.**

***Index Terms*—Human-robot interaction, modeling, simulation, social robots**

## I. Introduction

Recently, there has been much research into using social robots to communicate with people in real world environments. Social robots have been placed in museums [1] – [3], exhibition expos [4], reception areas [5], shopping malls [6, 7], transit stations [8, 9] and other public areas [10]. As these various experimental applications have shown, social robots have a promising future of not only attracting people by their novelty, but also being able to provide useful and reliable services in our daily life.

Supervision by a human operator is necessary when deploying social robots in the real world in order to: 1) ensure safety of both humans and the robot, 2) deal with unexpected situations, and 3) enrich the content of social interactions between humans and robots by incorporating an operator's knowledge and common sense. As the ever-increasing autonomy of robots enables more tasks to be done by automation, the operator's workload will be reduced, enabling multiple robots to be controlled using the operator's free time.

Choosing the proper configuration of a teleoperated social robot team is often difficult, because different factors affect the team dynamics, such as the level of robot autonomy, the time required for teleoperation tasks, and the number of robots to be used. Because awkwardly acting robots may give a negative impression to customers and bystanders [11], it is not desirable to try robot deployments with arbitrary settings in a real-world application – this would carry a high risk of losing customers in the long term. Therefore, it is necessary to predict the performance of a human-robot team prior to deployment.

The purpose of this study is to present a modeling technique for human-robot teams conducting short-term interactions, and to provide practical techniques and methods to optimize team performance. A previous study [12] gives a detailed description about interaction modeling, based on which we address more detail about implementation issues and further analysis in this paper. Techniques related to managing interaction flow and operator task assignment will be introduced. Then, we will discuss how simulation can be used to analyze the effects of these techniques and other factors by estimating fan-out and team performance under different conditions. Finally, a case study on deploying multiple robots in a shopping mall is presented to demonstrate the usefulness of our study in helping the design and implementation of social robots in real-world settings.

## II. Related Literature

The overall theme of this paper is to discuss two common issues existing in the study of social human-robot interactions. One issue is how to evaluate and improve the team performance of multiple social robots; the other is how to practically implement a human-robot team for social interactions based on current state-of-the-art technologies. This section is devoted to providing a brief survey about each of those issues. The first part discusses metrics for evaluating human-robot teams in previous studies, and the second part discusses the existing technologies which provide useful hints for the implementation of our system.

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This paper is an extension of a previous study in [12], to which we have added implementation methods for interaction management techniques and simulation, more analysis on metrics, and more detailed descriptions about the field trial.

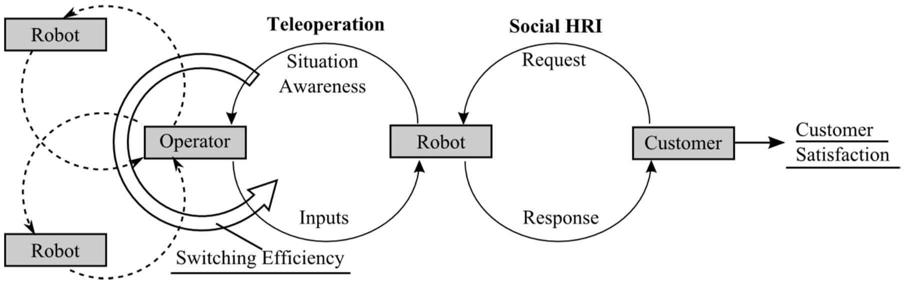


Fig. 1. Human-robot interaction model

### A. Metrics on Multi-Robot Control and Social HRI

Studies of human-robot team performance are related to various topics, such as situational awareness [13], adjustable autonomy [14] and mixed-initiative control [15]. For predicting team size and evaluating performance, metrics such as fan-out [16, 17], neglect tolerance [18] and interaction efficiency [19, 20] have been studied.

The "fan-out" metric represents the theoretical upper boundary for the number of robots that one operator can control based on aggregate task metrics such as interaction time and neglect time. In the problem scope of social robots, we find that by considering human factors such as a customer's frustration with delays in the robot's responses enables us to create a more refined model of fan-out for a human-robot team performing social interaction tasks. Pioneering studies on teleoperation of multiple social robots have been conducted, wherein metrics such as situation coverage and critical time ratio [21, 22] are introduced to measure task difficulty for a robot team in conversational interactions.

Besides quantitative evaluations, extensive studies have been conducted on the social psychological aspect of human-robot interactions. Dautenhahn [23] and Duffy [24] studied the effect of appropriate humanlike qualities applied to social robots. Sabanovic et al. [25] suggest evaluating social robots based on observational analysis, and proposed several salient factors for designing human-robot interaction, such as gaze, scaffolding and rhythmicity.

Determining an appropriate metric for evaluating social "effectiveness" is difficult, since the purpose and functionality of social robots differ in various applications [26], but a quantitative metric is still necessary for comparing the performance of a social robot team on various conditions as inputs to the system. This study will propose a metric based on waiting time of users in conversations with robots, and demonstrate its usefulness through experiments and a field trial.

### B. Technologies for Social HRI

While rapid progress has been made to improve robot intelligence, the lack of autonomy is still a major bottleneck in achieving more intelligent robots for social interactions. For example, a speech recognition system that performed with 92.5% accuracy in 75dBA noise [27] achieved only 21.3% accuracy in a real-world environment [9]. Hence, under current state-of-the-art technology, we still need to adopt human perception and intelligence to take control or recover from failures of automation.

Techniques have been developed to enable smooth transitions between automation and operation, or to enable robots to act less awkwardly under automation failures. A method called proactive timing control [21, 22] was developed to proactively adjust robot behaviors to delay the chance of automation failure before the operator is assigned. Conversational fillers [11] were studied to mitigate human frustration when robots cannot respond immediately in some conversations.

The studies above have provided us valuable clues on how to manage social interactions using semi-autonomous robot teams. In this study, we will discuss the usefulness of such technologies in managing waiting times of users during conversations with robots, and also introduce other technologies such as audio buffering to improve robot performance by reducing waiting time.

## III. Human-Robot Interaction Model and Metric

Fig. 1 illustrates the human-robot interaction model. We study human-robot teams consisting of a single operator and a certain number of semi-autonomous robots to conduct dialog-based social interactions with "customers". We use the term "customer" to refer to a person who engages in social interaction with a robot. This term has some similarity with Scholtz's role of "peer" [28] in that it represents the human side in a face-to-face interaction with a robot. But it differs from the "peer" or "teammate" role in that the human and robot are not collaborating to achieve a single goal; rather, the human's role as a *service receiver* in the interaction, in contrast to the robot's role as a *service provider*.

One thing to mention about our overall model is that here we use the term "Social HRI" to refer to human-robot interaction through short-term conversations. In terms of Newell's notion of bands of cognition [29], these short-term interactions correspond to the "cognitive band" of cognition, where we are concerned with individual utterances and speech acts for interactions that last for tens of seconds. Longer-term interactions in the "rational band" (minutes to hours) or the "social band" (days to months) will require additional considerations beyond the models presented in this study.

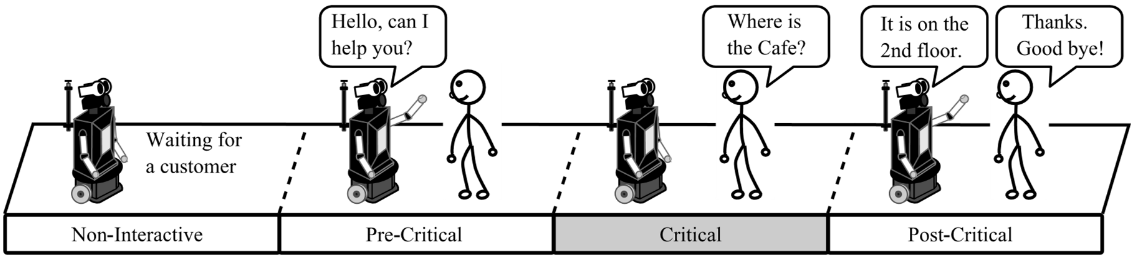


Fig. 2. Customer-robot interaction phases

*A. Operator Model*

In study [30], a human operator is modeled as a server in a single-server queuing network. In this paper, we model the operator as having the same role, whose job is to control robots in the situations which cannot be handled autonomously, or when a high risk of error exists in automation. To perform an operation, the operator should acquire situation awareness about the interaction between the customer and robot, and give proper inputs to control robot behaviors.

As in studies [17], [20] and [31], operation time (referred to as interaction time) is used to evaluate the performance of a human-robot team, which generally consists of the time for (a) gaining situation awareness, (b) problem solving (or decision making) and (c) command expression via the interface. In [32], the process of situation awareness is further defined by levels representing perception of elements in current situation, comprehension of the current situation, and projection of future status. But as mentioned in [17], these elements of interaction time occur mostly in the user's mind and are therefore difficult to measure directly.

To model the activities of the operator in a measurable way, we propose a simplified model which divides an operation into "listening" and "actuation" time as in (1). Listening time corresponds to the time for the operator to recognize the customer's request from audio data, and actuation time corresponds to the time from the end of listening to the end of an operation. Notice that listening time may not be equal to the time for situation awareness, and actuation time does not only represent the time for command expression, because problem solving can happen at any time during an operation.

$$t_{operation} = t_{listen} + t_{actuation} \qquad (1)$$

The benefit of this modeling is that each part of operation can be measured or estimated separately, and then a reasonable estimation of total operation time can be calculated based on the estimates of each part. Section IV-C will give an estimation method for listening time based on the customer's utterance time, and Section IV-D will discuss the estimation of actuation time when various types of input methods exist in the operation interface.

*B. Customer-Robot Interaction Model*

A customer-robot interaction progresses by the exchange of requests and responses between a customer and a robot. Previous work shows that conversational human-robot interactions tend to follow certain patterns [22], providing the possibility of predicting the next step in advance based on the current state of a conversation. As illustrated by Fig. 2, we model the customer-robot interaction by dividing an interaction into phases representing unique states in an interaction:

- **Non-Interactive Phase**: This phase is when the robot is in an idle state and waiting for customer arrival.
- **Pre-Critical Phase**: This is the phase when a customer arrives and the interaction can be handled automatically. It includes automatic detection of customer arrival and behaviors like greeting or making a self-introduction by the robot.
- **Critical Phase**: This phase is when an operator's attention is needed because of a high risk of error by automation. This phase starts when it is the customer's turn to speak, because the operator is needed from that time in order to recognize the customer's request and make a correct response.
- **Post-Critical Phase**: This phase is when the operator's control is finished, and the automated system handles the execution of behaviors to finish the interaction.

The key concept in this modeling is that an interaction can be divided into *Critical* and *Non-Critical* phases, determined by whether or not the operator's attention is needed. Using such definitions, we can manage the teleoperation of multiple robots by allocating the operator only to the robots in critical phase, which will be explained in detail in Section 4.

*C. Customer Satisfaction Model* In this study, we define "customer satisfaction" as a quantitative evaluation of the quality of simple short-term conversations between customers and robots from the customer's perspective. Previous research shows that customers get frustrated while waiting in a conversation with a robot, even if a correct response is eventually made by the robot after certain amount of time [11]. Based on this finding, we model customer satisfaction as a function of waiting time.

According to the customer-robot interaction model, there are two waiting times for a customer in an interaction: waiting for the robot to finish speaking in the pre-critical phase, which we designate as ($t_{before}$) , and waiting for the robot to respond after the customer has asked a question in the critical phase, which we designate as ($t_{after}$). We hypothetically model the drop in customer satisfaction as a linear function of wait times before and after the question as in (2), where satisfaction (S) has an initial value $S_0$ and drops with rates $\alpha$ and $\beta$ during wait times before ($t_{before}$) and after $t_{after}$( ) a question.

$$Satisfaction = S_0 - \alpha t_{before} - \beta t_{after} \qquad (2)$$

This model is defined for the ask-reply type of short-term dialogs as defined in the previous sub-section, and is based on an assumption that a correct and socially acceptable response can be made by the operator's manipulation. The parameters $\alpha$ and $\beta$ reflect the different drop rates of satisfaction, which can be affected by various psychological and environmental factors related to the type of interaction. Among these factors, we find the context (or topic) of conversation is an important factor in determining $\alpha$ and $\beta$, reflecting the general complexity of questions and affecting the customers' expectations toward the robot's response time. In Section V, we will measure the parameter values from data collection with two different contextual settings, and we will discuss the difference of the parameters in reflecting the complexity of the two conversation contexts.

Regardless of conversation context, we believe that $\alpha < \beta$ in general, because the time waiting for an answer is more critical than the time waiting before asking a question, causing more anxiety and frustration to the customer. This hypothesis, along with the validity of the linear model, will also be verified in Section V.

### D. Situation Coverage Metric

Situation coverage was discovered to be a very important metric regarding the performance of teleoperated social robots in previous studies [21, 22]. It is defined as the percentage among all interchanges between customers and robots, for which appropriate behaviors are prepared for the robots to respond.

A situation is "covered" when the robot has a built-in behavior to respond to the customer's request, and such a behavior can be triggered immediately by the operator using corresponding inputs through the UI, such as by clicking a button. A situation is "uncovered" when there is no such built-in behavior, which requires the operator to improvise a response using lower-level inputs, such as by typing an entire phrase for the robot to speak. Thus, responding to uncovered situations generally takes much longer than responding to covered situations.

Situation coverage results from interactions between a customer and a robot, and it influences the robot's response speed by determining the efficiency of inputs on the operator's side. A higher level of situation coverage is always preferable for an application, because in such case a larger proportion of operations can be performed quickly, resulting in shorter customer wait time on average and enabling more robots to be operated simultaneously. But even for a well-prepared system, uncovered situations may occur, since customer questions can be difficult to predict before the robots encounter real customers. We will perform a concrete analysis about the effects of situation coverage on the performance of a human-robot team in the following sections.

## IV. Interaction-Management Techniques

In this section, we present the key techniques which enable us to build an efficient system for operating multiple robots in dialog-based interactions. First, we define the problem we are going to solve, which is managing the conflicting demands for operator attention among multiple robots. Then, we introduce techniques for addressing two key problems that arise from these conflicts. Finally, a switching algorithm will be presented that enables efficient teleoperation of multiple robots by integrating these techniques.

### A. Problem in Multi-Robot Control

Before discussing details of these techniques, we first define the problem in multi-robot control that we are going to solve. We believe that the major problem in the teleoperation of a multi-robot team is the handling of conflicts when multiple robots require operator attention (i.e. are in critical phases) at the same time.

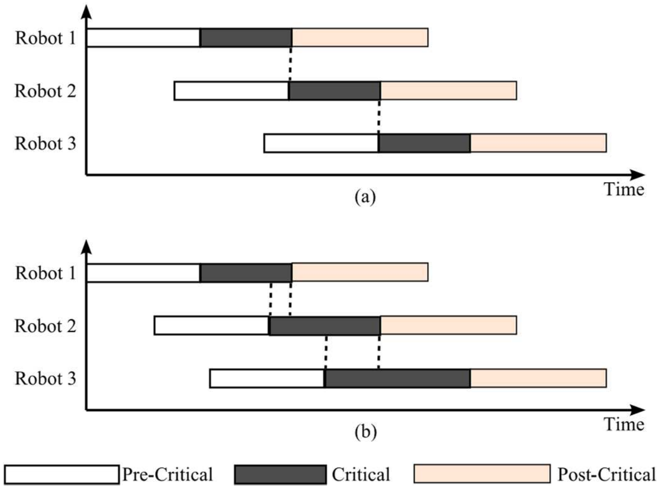

Fig. 3. Two examples of three simultaneous interactions

Fig. 3 shows two examples of controlling three robots, illustrating how interactions can conflict. Fig. 3(a) is an ideal case, wherein the critical phases are non-overlapping, and robots can be controlled in sequence by allocating the operator to the robots in critical phases. Fig. 3(b) is a more realistic case when multiple robots are interacting with customers at the same time. As we can see, the critical phases overlap with each other, resulting in conflicting demands for operator attention. The conflicts have two effects that may cause interaction failures:

1) The additional time spent waiting for an operator causes critical phases to get longer, making the customers wait a longer time after asking questions, which may result in failure to satisfy the customers.
2) A customer may ask a question to one robot while the operator is busy with another robot, so the operator may not be in time to hear what the customer has asked, resulting in a failure of operation.

Addressing the first problem, we adopted techniques from previous studies to mitigate customer frustration while waiting. To solve the second problem, we developed an audio buffering technique to prevent loss of information and enable efficient operation. Then using these techniques, a switching algorithm was developed that handles wait-time management and operator assignment as an integrated system.

### B. Wait-Time Management

Two mechanisms can be applied from previous studies to mitigate customer frustration during long waiting time, which we refer to as *Wait-Time Management*.

#### 1) Proactive Timing Control (PTC)

Proactive timing control [21] is a technique that dynamically adjusts the timing of interactions in order to prevent conflicts when two or more robots need operator attention at the same time. PTC can be defined as a sequence of robot behaviors performed in the pre-critical phase to delay the entrance to a critical phase, such as utterances and gestures which keep the robot talking for a planned amount of time.

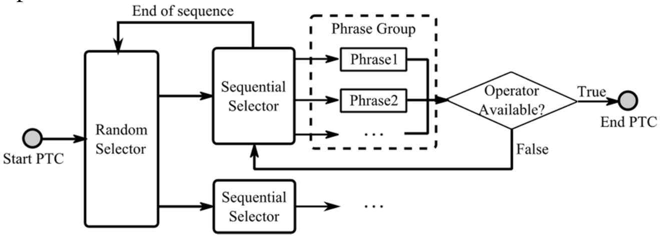


Fig. 4. An implementation of proactive timing control

An actual implementation of a proactive timing control module can be described by Fig. 4. A "phrase group" is a core functioning unit in a PTC module. It is composed of a sequence of logically connected phrases, designed such that stopping the utterance after any phrase will still make sense in a conversation. An example phrase group and some of its phrases are listed below:

> Phrase Group:
> - Phrase 1: Today is the shopping mall's anniversary. - Phrase 2: There are many interesting events.
> - Phrase 3: I can tell you about any of them.
> - Phrase 4: And I can give directions as well.
> - Phrase 5: …

The execution of a phrase group is controlled by a "sequential selector", which determines whether to stop or continue PTC based on the operator's availability. If the operator is available (i.e. has free time to control a robot), then PTC can be stopped, and the robot can proceed to the critical phase. Otherwise, the sequential selector will select the next phrase in the group to continue PTC. Phrases in a group are designed to be short enough that the time length of PTC can be controlled at a fine level of granularity. The detection of operator availability will be explained later when we present the switching algorithm.

As a phrase group only contains a finite number of phrases, multiple phrase groups can be prepared to cope with the case when the operator is still unavailable after the execution of a whole phrase group has finished. A "random selector" is used to randomly select a group after each execution of a phrase group. The reason for randomly selecting a group is that there are often bystanders when the robot is talking to a customer, and this random variation can help avoid giving customers the impression that robots are always saying the same thing when meeting any customer.

Proactive timing control can effectively prevent conflicts between critical phases. When multiple interactions are about to enter critical phases, the robots that cannot be attended by the operator will perform PTC to delay the entrance to the critical phase. From a customer's perspective, PTC is executed before asking any question, while it is still the robot's "turn" to speak, and thus the extra behaviors seem to naturally integrate into the flow of interaction.

#### 2) Conversational Fillers

Conversational fillers have been studied in [11] as a technique to mitigate a customer's frustration while waiting. They can be used in critical phases when the customer has finished asking the question, but when it will still be some time before the operator will finish operation. During such time, the robot can use conversational fillers to mitigate the customer's frustration by saying phrases such as "well...", "let me think...", "you know...", or "uh..." Experiments [11] show that conversational fillers successfully moderate customers' negative impressions towards long wait times.

### C. Audio Buffering

Audio buffering is a technique to prevent loss of information and enable operators to respond quickly when critical phase conflicts happen. The audio from the conversation between the customer and the robot is recorded into a buffer for each robot, thus even if the operator switches to a robot after the interaction has begun, it is still possible to listen to everything the customer has said.

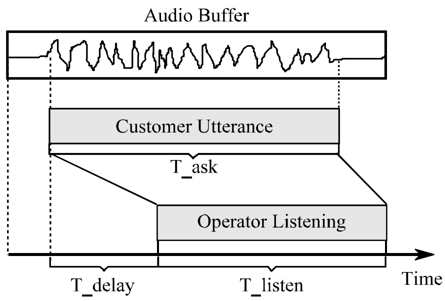


Fig. 5. Audio buffering and operator listening time

Fig. 5 illustrates the implementation of audio buffering. When the robot has finished speaking, it is assumed that the customer utterance begins, and the buffer begins recording audio. If the operator is switched to that robot sometime after this point, buffered audio is played back from the start of customer utterance.

Buffered audio can be played with faster speed while maintaining audibility, which enables the operator to spend less time to listen than the actual customer utterance duration. If we let K denote playback speed, then listening time ($t_{listen}$) is a function of operator delay ($t_{delay}$) and customer asking time ($t_{ask}$), as in (3). The maximum is taken because listening can't end before a customer finishes asking a question.

$$t_{listen} = \max\{t_{ask} - t_{delay}, t_{ask}/K\} \quad (3)$$

Audio buffering can help ensure that no loss of conversational information occurs when the operator is switched to a robot after the critical phase has started. In addition, by using fast-playback, the operator needs less time to listen to a customer's question, which shortens the overall operation time.

### D. Switching Algorithm

We next present a switching algorithm used in our teleoperation system which handles automatic operator assignment and robot phase planning based on the previously introduced techniques.

#### 1) Basic Mechanism

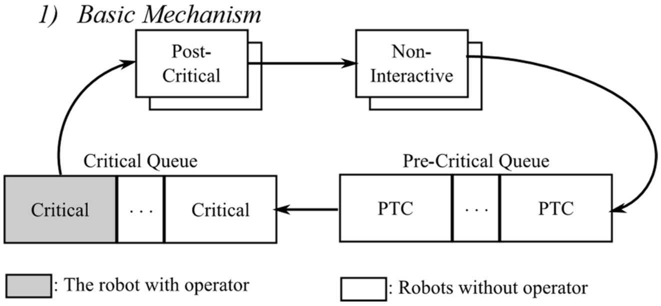

Fig. 6. Queuing of robots for operator assignment

As in Fig. 6, two FIFO queues, called the "pre-critical queue" and "critical queue," are maintained for robots in pre-critical and critical phases, sorted by phase start time. The operator is always assigned to the robot at the head of the critical queue, which is the first robot that started the critical phase.

There is a function for detecting whether an operator is available, which returns "true" if the operator can be assigned to the robot on time, and "false" otherwise. Using fast-playback, the critical phase can actually start slightly before the operator is assigned, by an amount equal to $(1 - 1/K)$ of the customer asking time, because the operator's listening time is $1/K$ of the asking time. Hence, by comparing the estimated operation time of the robots in the critical queue against $(1 - 1/K)$ of customer asking time, the decision of operator availability for a robot in the pre-critical queue can be made as follows:

```
FUNCTION Is-Operator-Available (Robot R)
  If (R is the head of pre-critical queue)
    If ( Σ_i^{Critical queue} t̃_operation(i) ≤ (1 − 1/K) · t̃_ask )
      Return true;
    Else
      Return false;
  Else
    Return false;
End
```

Here, $\tilde{t}_{operation}(i)$ is the estimated operation time for i-th robot in the critical queue, which will be compared with start-ahead time to decide whether to let a robot proceed to the critical phase. To utilize the algorithm, we need a valid estimation of operation time before operation has actually begun. As in (1), we model operation time as a combination of listening and actuation times, wherein listening time can be given from the estimated customer asking time, operator delay, and audio play-back time, as in (3). The next subsection will discuss an estimation method for actuation time.

#### 2) Estimation of Actuation Time

In this section, we discuss the method of estimating an operator's actuation time when multiple input methods exist in a teleoperation interface.

In a teleoperation interface, there can be multiple input methods with different layouts and functionalities, and usually it is impossible to tell in a deterministic way which one will be used until the operation has begun. But if we acquire the knowledge about the probabilities of each input method to be used from statistics of a large number of operations, we can make a best estimation of operation time in a probabilistic way.

Suppose there are *n* different input methods, and the probability distribution of actuation time for each input method is known. Let $p_i$ denote the probability of the *i*-th input method to be used. Then, a penalty function in terms of loss of satisfaction can be defined by (4), where $t_e$ and $t_a$ denote estimated and actual actuation times, and $\alpha$ and $\beta$ are the penalties in customer satisfaction incurred when wrong estimation increases customer wait time, according to (2).

$$Q(t_e, t_a) = \begin{cases} \alpha(t_e - t_a), \text{when } t_e > t_a \\ \beta(t_a - t_e), \text{otherwise} \end{cases} \quad (4)$$

If we let $E_i[Q(t)]$ denote the expected penalty for input method *i*, then we can calculate it by integrating the penalty value over the entire time span for actuation time assuming the probability density function of actuation time is known. For simplicity, we use a normal distribution to represent the distribution of actuation time for each input method. Then, the expected penalty for the *i*-th input method can be calculated by (5), where $f(x; \mu_i, \sigma_i^2)$ is the probability density function of a normal distribution $N(\mu_i, \sigma_i^2)$ for the actuation time of the *i*-th input method. Although other distributions can be used for modeling actuation time, as will be discussed in the section of operator data collection, the normal distribution is sufficient for describing operator actuation time in this study. The expected penalty for estimation *t* is the expectation from all possible input methods weighted by the probabilities of their use, as in (6). The safest estimate of actuation time ($\tilde{t}_{actuation}$) is taken as the time which minimizes the expected penalty, as in (7). Finally, the estimated operation time can be calculated as the sum of listening and actuation time, by combining (7), (3) and (1).

$$E_i[Q(t)] = \int_0^\infty f(x; \mu_i, \sigma_i^2) Q(t, x) dx \quad (5)$$

$$E[Q(t)] = \sum_{i=1}^{n} p_i E_i[Q(t)] \tag{6}$$

$$\tilde{t}_{actuation} = \arg \min_{0<t<\infty} E[Q(t)] \tag{7}$$

As an example, Fig. 7 shows the expected penalties measured by satisfaction values when there are three input methods, namely simple choice, list choice and typing (see Sec. V-C for detailed explanation about each input method), each with actuation time being $N(1.9, 0.6^2)$, $N(3.1, 1.9^2)$, $N(32.9, 11.9^2)$ seconds, and have the same probability ($1/3$) of being used. As the figure shows, when estimating actuation time to be 22 seconds, the expected penalty is the minimum, which is the best estimation.

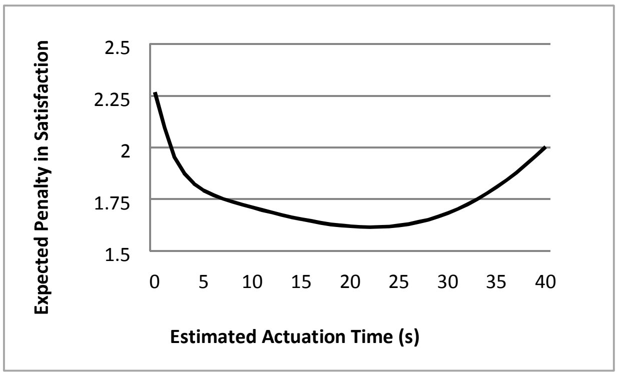


Fig. 7. Estimation of actuation time and expected penalty

## V. Measuring Model Parameters: User Study

### A. Scenario

Data collections were conducted to obtain human data for our models of the customer and operator. To investigate the impact of complexity in dialog-based interactions, two scenarios were used.

- **Guide scenario**: We assume that robots are working at a shopping center to provide route guidance. Customers ask questions about where some shops are, and robots answer the locations accordingly.
- **Seller scenario**: Robots are assumed to be working as sellers at a PC shop. Customers come to ask various questions related to PC's or peripherals, and robots provide accurate answers. Generally, such questions have higher complexity compared to the first scenario. The first scenario represents a context in which customers are in a hurry and interactions are short. The second one is about a relatively complex scenario, when customers are not in such a hurry but need detailed information.

*Portrait of participants*

Undergraduate Japanese students were recruited for data collections regardless of whether they had any background in robotics. We did not allow the same participants to take part in both data collections for operator and customer, because knowing how robots are operated may affect a participant's evaluation when acting as a customer. Basic computer skills for daily life were required for participants acting as operators.

### B. Customer Data Collection 1) Procedure

Fifteen people participated (8 female, 7 male, mean 22 years old). Each participant took part in both scenarios. For each scenario, participants performed 16 interactions with a robot by asking different questions.

Two aspects of the robot's behavior were varied between interactions. First, the duration of the robot's speech preceding the asking of the question, which corresponds to the time when PTC behaviors would be executed, was varied among 0, 15, 30, and 45 seconds. Second, the delay until the robot responded to the question in the Critical phase was varied among 0, 5, 10, and 15 seconds. Conversation fillers were used during this waiting time. In total, this resulted in 16 variations of timing settings. After each interaction, participants evaluated their satisfaction with an integer value from -5 to 5, where -5 and 5 indicate maximum negative and positive satisfaction. Each scenario was repeated twice to counter-balance the ordering effect.

*2) Results*

Fig 8 shows the average satisfaction values for each scenario. The values form approximate planes in 3-D space, indicating that satisfaction is approximately linear in both PTC and wait time. By linear regression analysis using least squares, parameters of (1) were calculated as in Table I (decision coefficients $R^2$ are 0.970 and 0.967 for each scenario, which indicate very good fitting). Asking and answering times were also measured, where $\mu$ and $\sigma$ are mean and standard deviation.

TABLE I
Parameters from Customer Data Collection

| Scenarios | $S_0$ | $\alpha$ | $\beta$ | Customer Asking Time (s) | | Robot Answering Time (s) | |
|---|---|---|---|---|---|---|---|
| | | | | $M$ | $\sigma$ | $\mu$ | $\sigma$ |
| Guide | 3.65 | 0.07 | 0.18 | 4.1 | 1.4 | 5.1 | 0.6 |
| Seller | 3.68 | 0.04 | 0.14 | 5.8 | 1.8 | 10.6 | 1.7 |

It was verified that $\alpha < \beta$ for both scenarios, meaning people are generally more patient when waiting before than after asking. In the seller scenario, $S_0$ is larger and $\alpha$ and $\beta$ are smaller, indicating that customers tend to be more patient in that scenario. This seems to show that people's tolerance of wait time is different depending on interaction complexity.

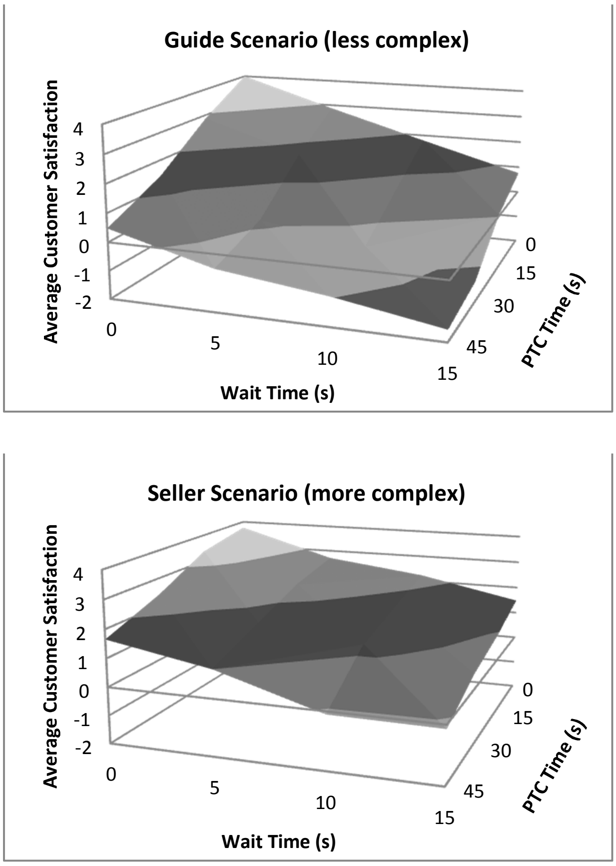


Fig. 8. Customer satisfaction in different scenarios

### *C. Operator Data Collection*

We conducted another data collection to measure actuation time for robot operators, as a function of the input method used.

#### *1) Procedure*

For the operator data collection, sixteen people (7 female, 9 male, mean 21 years old) participated in the two scenarios. Instead of setting up real robots and customers, we recorded audio from customer questions asked in the previous data collection, and used it to simulate customer-side interactions. To explore the effect of input method on actuation time, operation time was measured using three input types: binary choice, list choice and typing. For the binary choice interface, two choices, including the correct response, were shown. The list choice interface was similar, but instead 20 choices were shown. For the typing interface, the operator directly entered the answer into a text field. Actuation time was measured as the duration from the end of audio play-back to the end of each operation. Within each of the two scenarios, the mean and standard deviation were computed for the measured actuation times for each input method.

#### *2) Results*

Table II shows the result in terms of mean and standard deviation of actuation time for each input type. It is necessary to find a mathematical model to approximate the distribution of actuation time in order to estimate operation time. One candidate is the normal distribution, which describes the distribution when most actuation times fall near a mean value and are symmetrically distributed. Another candidate commonly used in queueing theory [33] is the exponential distribution, which assumes an equal probability of actuation finishing at any moment, resulting in a long-tailed probability distribution. From an examination of the measured data points, we found that the normal distribution closely fits with our data set, and thus we used it as an approximation of actuation time distribution in this study.

The data collection results indicate that the input method greatly affects the operator's actuation time. Actuation time increased as the complexity of operation increased, with typing time substantially longer than the other two input methods, and selection from list choices took longer than binary choice. The operation of the seller scenario took longer than the guide scenario for each interface, which we attribute to the increased time required for both problem solving and command expression caused by the increased complexity of the conversation context.

In real-world applications, it is difficult to develop an interface in which all operations can be made by simple inputs, because of the difficulty of predicting what utterances will be necessary in a social interaction. Unexpected situations will require the operator to perform lower-level control such as typing. Hence, situation coverage, described in Section III-D, affects operation efficiency, as it influences the proportion of operations which can be made by simple or complex inputs.

TABLE II
MEASURED ACTUATION TIME FOR DIFFERENT INPUT TYPES

| Input Types | | Binary | | List | | Typing | |
|---|---|---|---|---|---|---|---|
| | | guide | seller | guide | seller | guide | seller |
| **Actuation Time (s)** | $\mu$ | 1.9 | 2.2 | 3.1 | 5.5 | 32.9 | 45.0 |
| | $\sigma$ | 0.6 | 0.9 | 1.9 | 4.8 | 11.9 | 18.5 |

## VI. INTERACTION STUDY USING SIMULATION

This modeling enables us build a simulation tool for studying social human-robot interactions in great detail. In this section, we will present the mechanism of the simulation tool, and present experimental results to validate its accuracy. Then, we will explore the effects of different techniques and configurations on the performance of a human-robot team using simulation.

### *A. Simulation Tool*

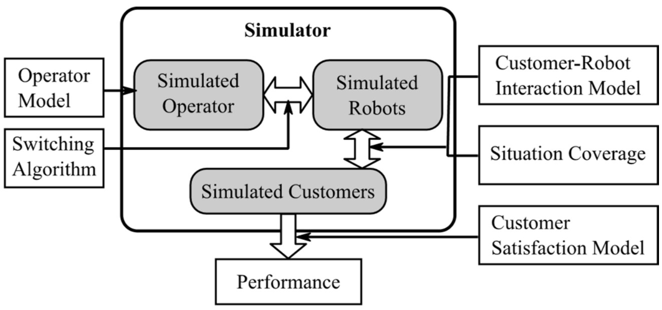


Fig. 9. Basic workflow of the simulator

Fig. 9 illustrates the basic workflow of the simulator. It is a computer program simulating a world of customers, robots, and an operator, and it simulates interactions among them based on timings specified by interaction models. Interactions between customers and robots are simulated using a customer-robot interaction model (Sec. III-B), which specifies the structure of interaction phases and durations of each phase. Situation coverage (Sec. III-D) is an adjustable variable which specifies the proportion of customer requests that are quickly answerable. The operator model (Sec. V-C) specifies operation speed for different input methods, and the switching algorithm (Sec. IV-D) is simulated for allocating operator tasks. To generate the output of the simulation, the customer satisfaction model (Sec. V-B) is used to calculate performance resulting from the simulated interactions.

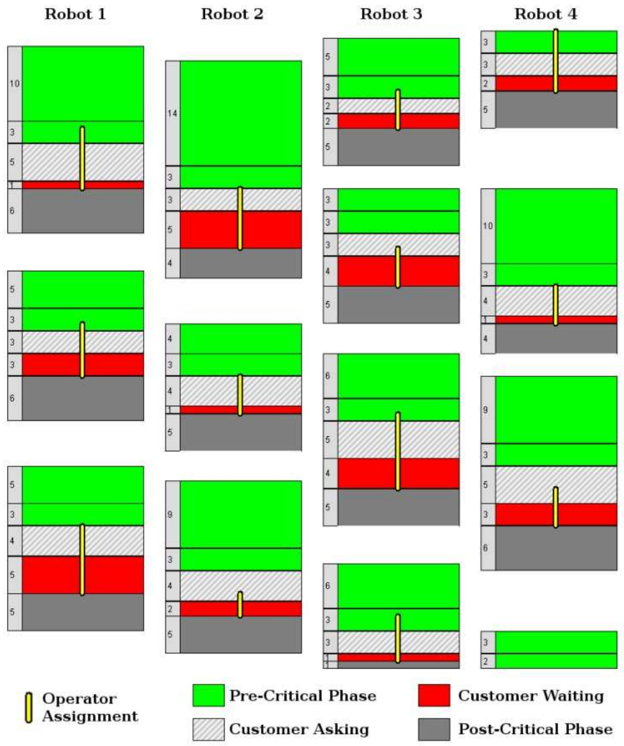


Fig. 10. Visualization of simulation

During execution, the simulation generates a timeline of interaction phases. Fig. 10 shows a visualization of one set of simulated interactions for a human-robot team consisting of one operator and four robots. Each column depicts the timeline of one robot's interaction phases with the numbers in the left-hand side indicating the durations of each phase in seconds. The process of each phase is simulated as follows:

- *Pre-critical phase*: Proactive timing control is simulated to control the length of this phase. This phase only proceeds to the next when the operator is available or anticipated to be available shortly, as described in Section IV-D.
- *Critical phase*: This phase includes the customer's question to the robot and the operator's response, including listening time and actuation time. The distributions of customer asking time and operator actuation time were obtained through data collection, shown in Tables I and II, and listening time is calculated using by (3).
- *Post-critical phase*: This phase includes the time required for the robot to execute answering behaviors. It is specified according to the scenario, designated as "Robot Answering Time" in Table I.
- *Non-critical phase*: We simulate frequent customer arrivals with a normal distribution of $N(5,2^2)$ seconds between interactions in all the simulations.

As the output of the simulation, customer satisfaction can be calculated using by (2), wherein the waiting times are counted as follows:

- $t_{before}$: the duration of pre-critical phase.
- $t_{after}$: the duration of operator's response time.

From the satisfaction results of the individual interactions, we calculate the team's performance as the sum of customer satisfaction from all robots per unit amount of time as in (8), supposing $N_r$ is the number of robots, $N_i$ is the number of interactions conducted by i-th robot, and $Satisfaction_j^i$ is the satisfaction value of j-th interaction conducted by the i-th robot. This equation reflects the efficiency of the robot team in "producing" customer satisfaction in a unit amount of time.

$$Performance = \frac{\sum_i^{N_r} \sum_j^{N_i} Satisfaction_j^i}{Total\ Time} \tag{8}$$

### B. Validation of Simulation

An experiment was conducted to determine whether simulation can provide a reliable result in comparison with human operators. Fifteen people participated (6 female, 9 male, mean 20 years old).

#### 1) Procedure

The validation was conducted by comparing the performance of robot teams (a) operated by participants and (b) from simulation, for each team size from 1 to 8. If the two conditions provide similar results for each number of robots, it will verify that simulation can provide trustworthy estimation. For condition (a), we did not set up real robots and customers, but instead recorded audio of people asking questions and used them to reproduce customer requests. By providing operators with an experience similar to that of real teleoperation, we expect that operation time will be similar to that for a real robot operation task. Since the objective of this evaluation was to verify if simulation can provide similar timing compared to human operators, such settings are enough to generate a valid comparison. For condition (b), the measured interaction timing parameters in Tables I and II were used in the simulation.

The guide scenario as described in Section V-A was set for both conditions. Situation coverage was set to 90%, with list choice and typing available for covered and uncovered situations, respectively.

*2) Results*

Fig. 11 shows the comparison of mean performance[1] from simulation and participants, where standard error of participant data is also depicted. Although slight differences in some data points exist due to variation of performance by participants, the changes of performance show the same trend, and both results indicate the fan-out being 3 by forming performance plateaus of similar shapes. Thus, we can conclude that simulation provides reasonable estimation regarding actual performance when using data measured from real interactions.

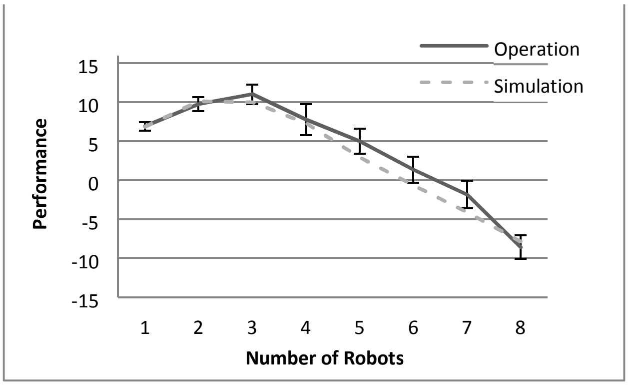


Fig. 11. Comparison of performance between human operators and simulation

### *C. Interaction Studies with Simulation*

We conducted simulations to explore the effect of different techniques and metrics on the performance of a human-robot team. First, we conducted validations on the effectiveness of using interaction management techniques such as fast-playback and proactive timing control. Then, we explored how metrics such as situation coverage and operation efficiency affect team performance. In the simulations described throughout this section, we examined the guide and seller scenarios described in Section V-A under 90% situation coverage, where operation using list and typing are simulated respectively for covered and uncovered situations.

*1) Validation of Estimation and Fast-Playback*

To validate the effectiveness of the operation time estimation and fast-playback techniques, simulations were conducted under three conditions on different numbers of robots for each scenario. For comparison, we simulated a baseline condition, in which neither technique was used – that is, robots were only permitted to enter critical sections when an operator was already available. Then, we compared it with the conditions of using only estimation and using both estimation and 1.5-time fast-playback. We did not set a condition of using only fast-playback, because the function of fast-playback necessarily requires estimating operation time ahead, hence it cannot be used without estimation. The average performance from 1000 simulations, each simulating a 10-minute teleoperation session, was calculated for each condition.

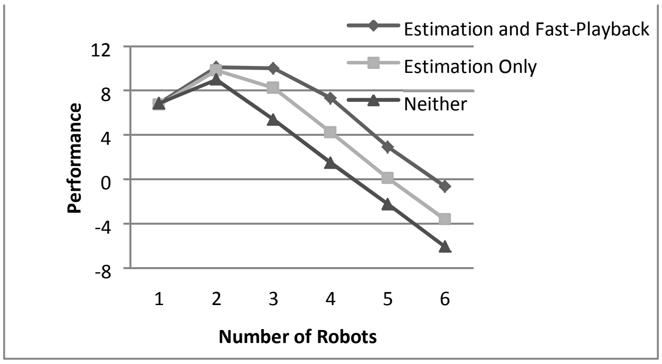


Fig. 12. Validation of estimation and fast-playback in guide scenario (The standard errors for each data point are between 0.04 and 0.13.)

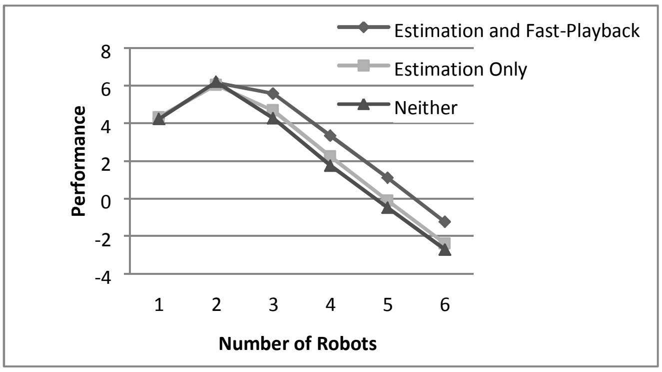


Fig. 13. Validation of estimation and fast-playback in seller scenario (The standard errors for each data point are between 0.03 and 0.09.)

Results in Fig. 12 and Fig. 13 indicate that both conditions using the proposed techniques outperform the baseline in both scenarios. The effect of estimation is most valuable when combined with fast-playback, because ideally the pre-critical phase can be shortened by $(1 - 1/K)$ times the asking time when playback speed $K$ is greater than 1. Even when not using fast-playback, estimation is effective because it alleviates the need for the operator to be present while to the robot is asking for the customer's question, which usually takes 2~3 seconds. However, as we can see in Fig. 13, the improvement in the "estimation only" condition is not as significant in the seller scenario as it is in the guide scenario. This is because of the higher variance of operation time in this condition (see Table II), which results in a higher likelihood of wrong estimation.

[1] Results regarding performance are expressed in units of "satisfaction per minute" throughout this paper.

*2) Validation of Proactive Timing Control*

We next examined the effectiveness of proactive timing control. For this comparison, we created a "No PTC" condition, in which interactions go into critical phase no matter whether the operator is available. We compared this with a "With PTC" condition, in which the pre-critical phase will last until the operator is available. Neither estimation nor fast-playback were used in this comparison. The average performance from 1000 simulations, each simulating a 10-minute teleoperation session, was calculated for each condition.

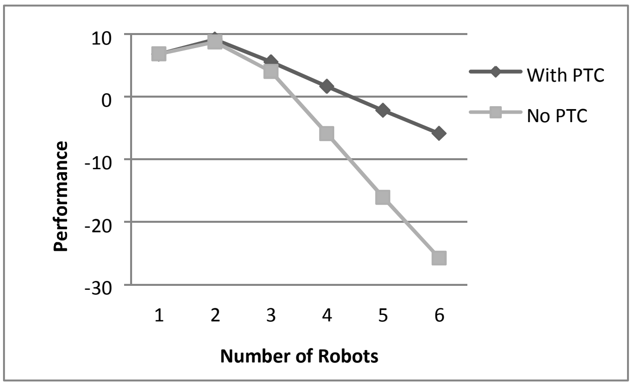


Fig. 14. Validation of PTC in guide scenario

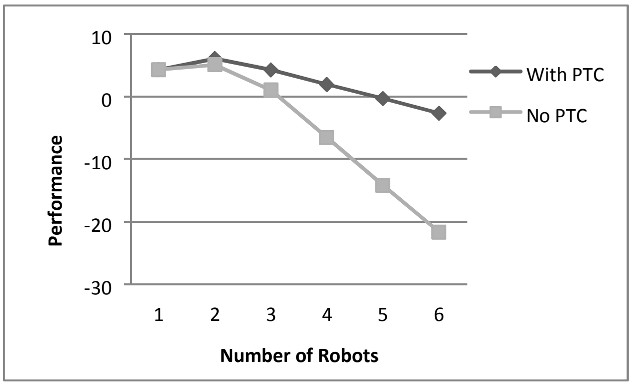


Fig. 15. Validation of PTC in seller scenario

Fig. 14 and 15 show the simulation results in each scenario. In both scenarios, the two conditions showed similar performance up to the number of robots for optimal fan-out (which was 2 for these settings), and then performance in the "No PTC" condition dropped severely for larger numbers of robots. The simulation results indicate that the drop of performance can be greatly reduced for larger numbers of robots when using PTC, because the customer's waiting time takes place mostly in the pre-critical phase, causing less of a drop in satisfaction compared with waiting in the critical phase.

*3) Effect of Situation Coverage*

We evaluated the effect of situation coverage by comparing situation coverage settings of 100%, 90%, 80%, 70% and 60% for the two scenarios. The 100% situation coverage condition represents the extreme case when all operations can be made using list choice, while 60% condition simulates a situation where a large proportion of operations need typing. The average performance from 1000 simulations, each simulating a 10-minute teleoperation session, was calculated for each condition.

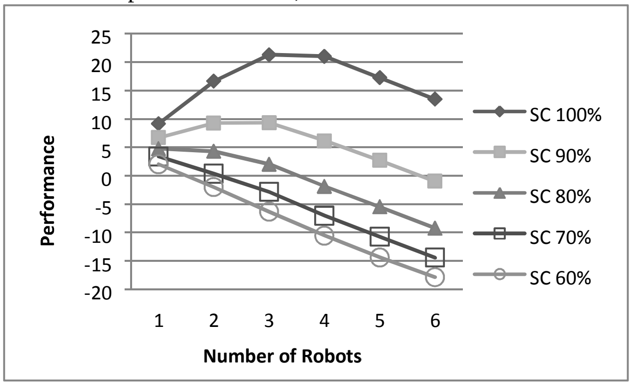


Fig. 16. The effect of situation coverage in guide scenario

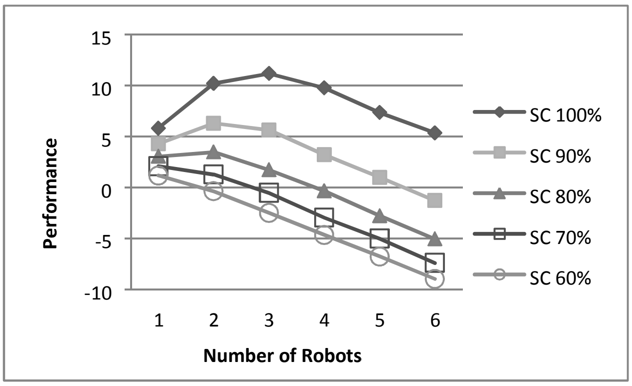


Fig. 17. The effect of situation coverage in seller scenario

As Figs. 16-17 show, the performance increases as situation coverage increases in both scenarios. The reason for this change in performance and fan-out is that situation coverage affects the statistical distribution of operation time. Equation (9) shows that the mean operation time can be estimated as the proportional expectation of operation time for covered and uncovered situations. For example, using the timing data from Table II, we can calculate the expected operation times in the guide scenario for SC values of 100% and 90% to be 3.1 and 6.1 seconds respectively, which means the operation speed when all situations are covered is almost twice as fast as for 90% SC, which results in a large improvement of performance.

$$\overline{t_{op}} = t_{op\_covered} \cdot SC + t_{op\_uncovered} \cdot (1 - SC) \quad (9)$$

*4) Effect of Operation Efficiency*

We next evaluated the effect of operation efficiency on performance by simulations with different values of operation time for the two scenarios. The baseline condition for this comparison used the operation times measured in data collection. We compared this with operation times 25% and 50% faster and slower. Situation coverage was set as 90% with list and typing inputs. The average performance from 1000 simulations, each simulating a 10-minute teleoperation session, was calculated for each condition.

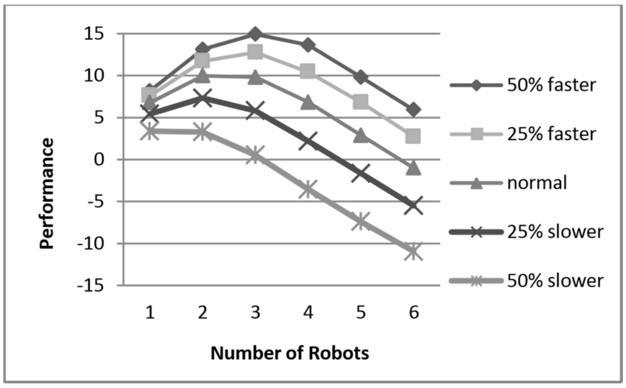


Fig. 18. The effect of operation efficiency in guide scenario

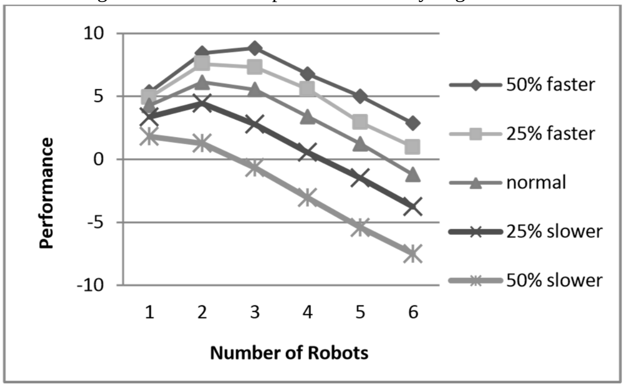


Fig. 19. The effect of operation efficiency in seller scenario

Figs. 18 and 19 show the simulation results in each scenario. Similar to the effect of situation coverage, change of operation time causes change of performance and fan-out, with faster operation resulting in higher performance and larger fan-out numbers. These results indicate that reducing operation time is an effective way of improving team performance. In practice, improvement of operation efficiency could come from interface design and training effects. A concrete example of improving operation efficiency through good interface design and operator training will be given in the next section.

## VII. Deployment Using Simulation: A Case Study

In this section, we present a case study in deploying multiple social robots for a real-world application. The research goal is to verify the effectiveness of simulation as a strong tool in each stage of the development process, which finally leads to a successful deployment of a human-robot team in the field.

### *A. Scenario*

A large shopping mall containing more than 80 shops and other facilities wanted to use social robots to attract customers by providing some useful service for its anniversary during a period of four days. Our task was to deploy robots which could provide services including route guidance and information provision given one month for preparation before the anniversary. Using a larger number of robots was preferable because they can attract more customers in the same amount of time, but the quality of service should also be guaranteed when the number of robots increases.

### *B. Setup*

ROBOVIE-II humanoid communication robots were used in our case study. The teleoperation interface for controlling the robots is shown in Fig. 20. It contains a text-to-speech component (area "a"), lists (area "b") of pre-built behaviors for answering questions, and a map interface (area "c"), by which the pre-built route guidance behaviors can be triggered when each button representing a shop is clicked.


Fig. 20. The teleoperation interface

### *C. Procedure*

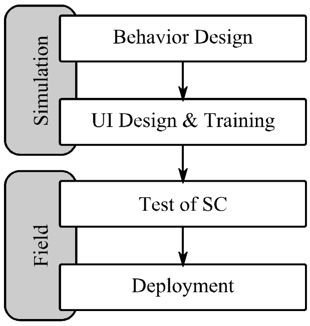


Fig. 21. The deployment procedure

We divided the deployment procedure into several stages with each stage focused on specific tasks, as shown in Fig. 21. The preparation stages include behavior design, UI design and operator training, wherein simulation was used to estimate performance and verify the completeness of each stage. The last two stages needed robots working in the field. A test of situation coverage was conducted before actual deployment, and robots were deployed for four days of the anniversary once good performance could be ensured through the previous stages. During the time when the robots were deployed in the shopping mall, real performance was measured based on customer waiting time.

### *D. Results*

We present the results of the whole process including preparations and field deployment. For the preparation stages, we state the tasks and how simulation was used to help our tasks in each stage; for deployment results, we show actual performance of robots working in the field.

*1) Behavior Design*

At the first stage, robot behaviors for answering customers' questions were designed and implemented. The target of this stage was to implement a sufficient number of built-in behaviors to achieve a certain level of situation coverage in order to enable more robots to be deployed.

We calculated the lower boundary of situation coverage necessary for different fan-out targets by simulating the performance using various values of situation coverage, as we did in Section VI. The model parameters for simulation were chosen from the guide scenario data in Table I-II, which

To gain some knowledge about the relationship between situation coverage and required number of robot behaviors, we refer to a previous study in [7], wherein a robot provided route guide service in a shopping mall. By implementing guide behaviors for all possible shops and facilities, situation coverage reached over 98% on average per day[2]. This indicates that the 91% situation coverage necessary for using three robots should be possible if we can implement enough behaviors. Since using more robots can attract more customers for the shopping mall, we set our target to use three robots, which is the maximum fan-out for this application when situation coverage is over 91%.

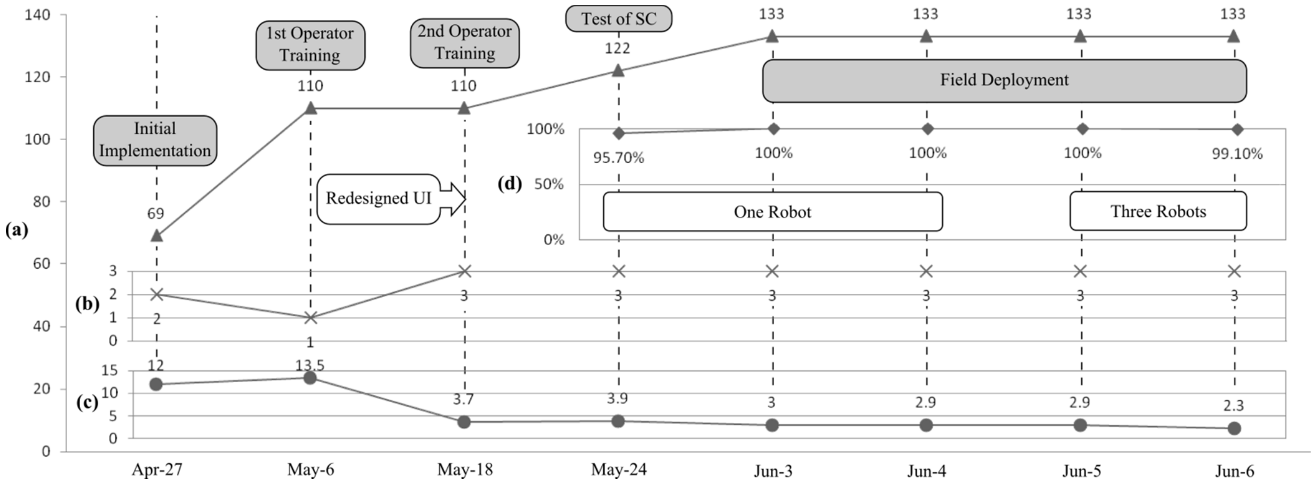


Fig. 22. (a) The number of implemented behaviors (▲), (b) Fan-out from simulation (×), (c) Mean operator actuation time for the list choice and map inputs (●), (d) Situation coverage (◆) during the field trial

corresponds to the scenario of our case study. One difference was that the system for our case study included a "map choice" entry interface, but no "binary choice." We modeled this difference by eliminating binary choice from the model and using the list input actuation time from the data collection for both map and list inputs in the case study, since the number of options in the map interface and the list interface were similar. We thus modeled list/map choice as being used for covered situations, and typing for uncovered situations. The results are shown in the first row of Table III, indicating that 40% situation coverage would allow operation of one robot with positive performance, 83% would enable two, and a maximum of three robots could be controlled with situation coverage of at least 91%. These results also show that even if situation coverage is increased up to 100%, four robots would not perform better than three.

TABLE III
MINIMUM SITUATION COVERAGE REQUIRED FOR DIFFERENT FAN-OUTS (WITH POSITIVE PERFORMANCE) IN GUIDE SCENARIO

| **Fan-out** | | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| **Lower boundary of SC** | **From data collection** | 40% | 83% | 91% | --- |
| | **1st operator training** | 52% | 99% | --- | --- |
| | **2nd operator training** | 41% | 84% | 91% | --- |

In Fig. 22, graph (a) shows the progress of the number of behaviors implemented during the field trial. 110 behaviors were implemented before operator training, and we gradually increased them up to 133 by the time of deployment, which included guiding behaviors for the shops and facilities in the shopping mall, behaviors for answering possible questions about the anniversary, and behaviors to play with children considering that many families with children would visit the shopping mall. As shown in graph (d), we were able to achieve 95.7% situation coverage with 122 behaviors in the test, and over 99.1% situation coverage was measured during the field deployment after increasing the number of behaviors up to 133.

*2) UI Design and Operator Training*

When the behaviors were designed, a corresponding user interface was implemented to control behaviors using three types of inputs: list choice, map selection, and typing, shown in Fig. 20. Here, the list choice and map selection inputs correspond to the operation methods for two types of covered situations: the list choice is for triggering play behaviors and

[2] We refer to the "knowledge provider" operations as uncovered situations in that paper.

answers to shopping mall information, and the map selection is for triggering answers to guide people to the locations of shops. Typing is still used to directly enter answers to questions which are not covered in the system. The operator was trained to manipulate the newly implemented UI, and the target of this stage was to get an acceptable operation speed which could result in fan-out of three robots as planned in the previous stage. Fig. 22 shows how our estimates of average operation time and potential robot fan-out progressed over time. When the full set of 110 behaviors and corresponding inputs had been implemented, we decided that most preparation for robot functionalities and operation interface were complete. At this point, we conducted a short period of operator training and measured operation time, revealing that the mean actuation time for list and map choices had increased to 13.5 seconds – much longer than in our initial data collection. We then conducted a simulation with the new operation times to evaluate whether the system was ready for the field deployment. As shown in Table III, this simulation indicated that 99% situation coverage would be needed to achieve a fan-out of two, and it would be impossible to make fan-out to be three even if the situation coverage reached 100%.

These predictions were disappointing, so we looked for the reason why predicted performance was so low. We found that the actuation time for the map inputs was extremely long, as shown in Fig. 23. Since these operation times did not enable us to meet our target fan-out of three robots, our development entered a re-design cycle. From the operator's feedback, we found that operation with the map was difficult because opaque buttons inhibited reading of the map. As a solution, we made the buttons semi-transparent as in Fig. 24, so that the operator could easily understand the locations represented by the buttons.

After conducting a second training with the redesigned UI, operation time was measured again. As indicated by Fig. 22 and Fig. 23, operation time was reduced significantly, with the mean actuation time for list and map inputs being 3.7 seconds. Based on these measurements, we once again used the simulation to compute the minimum SC required to attain different levels of fan-out. As the last row in Table III shows, these updated results were quite consistent with our original predictions based on the initial data collection. Based on the operator's improved operation speed, we now predicted that an SC of 91% would be sufficient for a fan-out of three robots.

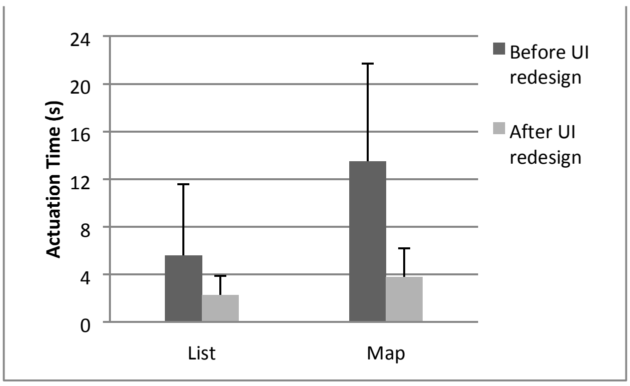


Fig. 23. Actuation time for list choice and map inputs before and after UI redesign


Fig. 24. Map UI before and after redesign

*3) Test and Deployment*

As situation coverage can only be measured from real interactions, a test in the shopping mall was conducted to see if the designed behaviors would result in high situation coverage by letting the robot meet customers before actual deployment. One robot was used for this test because the simulation results in Table III show that only 41% situation coverage was needed for one robot to get positive performance, which was an easy-to-satisfy condition when having the amount of behaviors prepared. Also by using one robot, we could minimize the risk of low performance caused by uncovered situations, and still make a valid test of SC from real interactions.

The test was conducted in one afternoon, and among 47 interactions with customers, 95.7% situation coverage was measured (Fig. 22), which was higher than our expectation of 91%, hence we could proceed to the final deployment of human-robot team.

Only one robot was deployed during the first two days of the anniversary. These days were weekdays, when very few customers typically went to the shopping mall, so multiple robots would have few chances to work simultaneously. Three robots were deployed on each of the last two days, which were weekend days when a large number of customers were expected. Fig. 22 shows the situation coverage, operator performance and fan-out from simulation during each day of deployment. From the figure we can see that the operator's actuation times stayed low during the four days of deployment, and since high situation coverage was retained, the fan-out predicted by the simulation remained at three robots each day.

Fig. 25 shows an example scene of three robots simultaneously interacting with customers during the field trial. Each column describes the actual phrases used in conversations between customers and robots [3], as well as the operator's activities during each interaction. As we can see, the second and third interactions started while the operator was still busy controlling the first, but through proper usage of proactive timing control, the operator had enough time to switch to the other robots later. In the third interaction, the operator was switched to the robot after the customer had already started asking the question, but since customer's voice was recorded into the audio buffer, the operator could still listen to it and control the robot to give the answer. As a result, the system could successfully handle simultaneous interactions by managing customers' wait time to achieve high satisfaction. Table IV and Fig. 26 show the number of interactions and customer waiting time measured on each day. In Table IV, we can see that waiting times before and after questions increased by up to 2 seconds for the three-robot case in the last two days, which would normally lead to lower satisfaction in individual interactions. However, as the robots conducted a larger number of interactions as a team, much higher team performance was achieved, compared with the single-robot case.

TABLE IV
CUSTOMER WAIT TIME AND NUMBER OF INTERACTIONS

| Days | | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| Mean Customer Wait Time (s) | Before[4] | 0.0 | 0.0 | 1.2 | 2.0 |
| | After | 3.6 | 3.9 | 5.3 | 5.0 |
| Number of Interactions | | 34 | 26 | 117 | 108 |

[3] For the robots, only phrases were listed in the figure, but the robots also executed proper gestures while speaking.

[4] The wait time before questions does not include the time for a robot to do a necessary self-introduction at the beginning of each interaction.

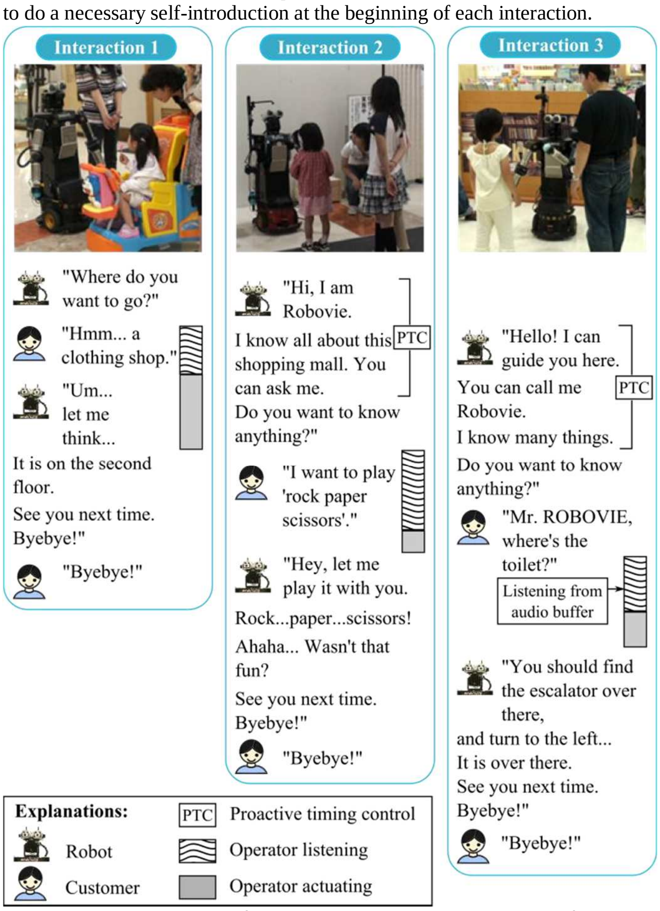

Fig. 25. An example scene of three simultaneous interactions in the field trial

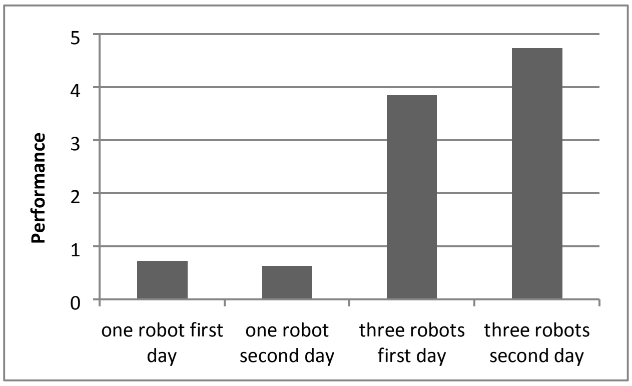

Fig. 26. Performance in each day of field deployment

*4) Summary*

By using the simulations based on interaction models in each stage of the deployment process, the following benefits were achieved:

*1. Ensuring Quality of Service*

Good service was ensured before the robots met real customers, because simulations were used to estimate performance before actual robot deployment. This feature is important for social robot applications, because putting robots outside without guaranteed performance may not only affect the current jobs, but also have the risk of making customers disappointed and lose interest in robots in the long term.

*2. Saving Development Time*

Development time was saved because we were able to calculate the minimum required achievement for each stage using simulation. For example, once situation coverage was confirmed to be high enough to achieve the fan-out target, no more behavior development was required. Without such a "doneness" criterion, it is difficult to decide when to stop the behavior development process. Another example was when the operator's performance was confirmed by the simulation to be good enough to achieve the fan-out target, after which no more interface design or training was required. In real-world projects, time and resources for development are often limited, and the ability to predict system performance and identify minimum requirements can help in planning and managing resources efficiently.

## VIII. DISCUSSION

### *A. Design Implication*

This study demonstrated the possibility of modeling conversational human-robot interaction dynamics and using simulation for predicting the optimal robot-to-operator ratio in advance of actual robot deployment, as well as for managing the development process of social robot applications. The type of application determines the expected duration of utterances and the wait tolerance of the customers. As shown by the data from user study, simple dialogs often have short durations of speech, both for questions the customer asks and for responses the robot gives, and customers have a low tolerance for waiting. In contrast, complex dialogs often have longer durations of speech and customers have a higher wait tolerance. Such model parameters of dialog duration and customer tolerance for wait time can be measured for a given application scenario.

The design of UI affects the operator's performance. If we can prepare quick-to-actuate inputs for many situations, we can expect better performance. The metric of situation coverage is associated with overall operation time by indicating the proportion of interactions that can be responded to using quick inputs versus inputs that are slower to actuate.

The level of situation coverage that can be achieved is a critical factor in determining the optimum robot-to-operator ratio for an application. If higher situation coverage can be obtained, it means a larger proportion of operations can be quickly made using simple inputs, and thus more robots can be controlled with optimum performance. But increasing situation coverage carries a cost in terms of effort to prepare robot behaviors, and such cost can be ever-increasing as higher situation coverage is required. For example, the number of robot behaviors to increase situation coverage from 90% to 100% would be much larger than that of increasing it from 40% to 50%, because a huge number of behaviors should be prepared for various kinds of rarely-happening but possible situations. Therefore, we need to carefully consider the trade-off between the effort to increase situation coverage and the performance gained from such effort.

### B. Fan-out as a Function of Individual Operator

In this study, we modeled operation time using average values taken from a group of subjects, but the difference in performance among individuals is also an important factor affecting fan-out. This is indicated by the fact that standard deviations of performance on subjects were very large in our experiment to validate the simulation (Sec. VI-B). This means that even though the simulation provided accurate prediction of fan-out on average, variations in operation capability between different operators may result in different levels of fan-out that can be attained.

The dependency of fan-out on operator performance is also reflected in the discussion of operator training in the case study. The operation for the list and map inputs was slow at first, which resulted in a maximum fan-out of only one robot. Then, after redesign of interface and more training for the operator, the fan-out increased to three robots. The list inputs were not redesigned throughout the measurements, but the operation speed still increased, which indicates the training effect. Therefore, to get more accurate computation of fan-out, we can use simulation for an operator based on individual measurements taken directly from that operator; even for the same operator working on the same UI, measurement should be updated after training has been conducted.

### C. Possible Extension of Situation Coverage

A situation is defined to be either covered or uncovered as a binary value, but we think it is possible to extend this concept for more complex situations. For a covered situation, there can be more than one way for an operator to address it, such as the list choice and map interfaces used in the case study. The operation with the map took longer time than with the list, which means the situations that can be handled by list and map caused different consequences on operation time. Hence, a finer-grained division of situations might be needed to predict the distribution of operations more accurately.

### D. Limitations and Future Work

We modeled operation time by implicitly including operator's thinking time into the component of actuation time. This approach proved to be useful for estimating operation time in the short-term interactions addressed in this study, wherein the operator's job is mainly speech recognition, and tasks such as problem solving or logical thinking are not considered. But as the complexity of operation increases, an improved modeling of operation time might be needed to consider the increased workload in problem solving. This may include more precise modeling of the various components of operation time and their probability distributions.

In this study, we modeled customer satisfaction as a function of the absolute wait times of the customer during different conversation stages. However, it seems possible that the drop in customer satisfaction could actually be a function of the difference between expected and actual wait times, and an extension of the model to consider this possibility might produce more accurate predictions of customer satisfaction.

The interaction models proposed in this study focus primarily on timing, and they do not consider other psychological or environmental factors such as interaction spaces, gaze, or scaffolding, which in some cases may significantly affect the results of interactions [25]. Due to this limitation, the usability and effectiveness of the models and interaction management system should be carefully considered in the context of the target interaction scenario.

## IX. Conclusion

We have achieved practical modeling of human-robot teams for conversational interactions, which enables us to describe operator and robot activities, and to predict customer satisfaction from interactions. We have introduced several techniques, which we have demonstrated to be useful in managing wait time during interactions and in enabling smooth assignment of tasks to an operator. A simulation tool was developed to predict the fan-out and performance of a human-robot team. This simulation tool has enabled us to study the impact of various factors on the effectiveness of multi-robot control, and to make valid predictions of team performance without actual robots. A case study was conducted to show the usefulness of simulation in the deployment process for social robots in a real-world project. Overall, we believe that this study provides a powerful method of designing a teleoperation system for controlling multiple social robots.

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