

Distributed Stochastic Resource Allocation in Teams

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Abstract—Motivated by Naval Battle Group tactical operations and by distributed product distributions and supplies, this paper considers distributed dynamic resource allocation within a two-person team. Having different but overlapping responsibilities, two geographically separated human decision makers (DM's) are to process multiple types of randomly arriving tasks with a set of renewable resources. To maximize the team reward for task processing, the DM's must coordinate on the assignment of common tasks (tasks of joint responsibility) and on the transfer of resources. A normative-descriptive approach is adopted to describe human decisionmaking process in the above setting. The approach starts with a normative model that predicts the team's optimal decision making, and a human-in-the-loop experiment that generates experimental data. Human limitations and cognitive biases are then identified to explain differences between model predications and experimental data. Incorporating human limitations and cognitive biases into the normative model, a normative-descriptive model is obtained. This model matches experimental data in almost all measures, and provides insights to human decision-making behavior.

I. INTRODUCTION

MOTIVATED by Naval Battle Group tactical operations and by distributed product distributions and supplies, this paper considers two-person human team resource allocation in a dynamic environment. The team is required to process multiple types of randomly arriving tasks that have different values, processing resource requirements, time requirements, and deadlines. Having a different but overlapping task responsibility, each decision maker (DM) is to process his/her tasks or those of shared responsibility with multiple types of renewable resources. These resources have multiple capabilities to support the needs of more than one DM, and can be transferred between DM's subject to time delay. Since each DM has tasks of various rewards and resource requirements at any particular time, coordination is needed to assign common tasks (those of joint responsibility) to individual DM's, and to transfer resources so as to maximize the total team reward.

Previous work in engineering and psychology related to this topic includes the general aspects of system theory,

decision theory, team theory, game theory, cognitive psychology, and behavior science. Some researchers ([1], [3], [19],[4], [14], [23]) concentrate on the normative modeling of resource allocation and team behavior, while others ([8], [13], [20], [21]) focus on the descriptive modeling of human decision making. It is known that a purely normative approach does not reflect actual human performance, whereas a purely descriptive approach does not have predictive capability for situations in which there is no directly applicable data. The normative-descriptive modeling approach ([17], [9], [15], [5], [2]) fuses normative and descriptive modeling efforts; it is the approach followed in this paper.

The basic hypothesis of the normative-descriptive approach is that well-trained DM's strive for optimality, but are constrained by inherent human limitations and cognitive biases. The approach starts with a normative model that generates the optimal solution. Model-driven experiments are then designed and operationalized, from which data are collected and analyzed. The normative model predictions are compared to experimental data. Significant differences are attributed to human limitations and biases, and are modeled by descriptive factors to produce a normative-descriptive model. Results from the modified model are compared with experimental data for significant differences. This iterative process continues until significant differences between model results and data are eliminated. The final normative-descriptive model thus captures human decision-making behavior. It is also valuable in understanding 1) the cognitive limitations and biases that constrain DM's performance, 2) the mechanisms that they use to cope with the task environment, and 3) the heuristic rules that they utilize.

In this paper, a normative model is developed in Section II. This "purely" normative model, however, is mathematically intractable. By incorporating a few well-known descriptive factors, a preliminary normative-descriptive model is developed in Section III. Driven by the model, the experimental paradigm Distributed Resource Allocation and Management (Dream) is designed and operationalized. This empirical effort is described in Section IV. In Section V, preliminary model results and experimental data are compared. The model-versus-data differences lead to the identification of one more descriptive factor. This factor is then included to form the final normative-descriptive model, whose predictive capability is examined. Concluding remarks are given in Section VI.

The contributions of this paper lie in the formulation of a quantitative model capturing key ingredients of distributed

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resource allocation in teams, the identification of a descriptive factor influencing human team decision making, and the development of the normative-descriptive model and corresponding constrained optimization algorithms describing the human decision making process.

II. A NORMATIVE MODEL FORMULATION

By assuming that each DM has the same global information and solves the same team optimization problem, a discrete-time model is developed as follows.

A. The Task State

In the problem, I types of tasks arrive randomly. A type i task, $1 \leq i \leq I$, is characterized by $\hat{r}(i)$, and M -vector representing the amount of M types of resources required to process the task; $T_r(i)$, the time required to process the task; $T_{ao}(i)$, the initial time available of the task (a random variable); and $g(i)$, the value of the task. Each task is preassigned. It can be DM 1's or DM 2's task, or a common task that can be processed by either DM. The task responsibility is indexed by $p = 1, 2$, or c .

After arriving, a task remains within an opportunity window for a certain time, within which it can be processed. At time k , the amount of time remaining for a task to reach its deadline is called the task's "time available" j , which decreases monotonically from $T_{ao}(i)$ to zero as time elapses. Since a task's characteristics are uniquely determined by its type (static feature), its time available (dynamic feature), and its responsibility index, a triple (i, j, p) is used to denote a type i task with j units of time available and responsibility index p .

Let the "active task set," $S^p(k) \equiv \{(i, j, p)\}$, be the set of arrived and yet unprocessed tasks (the so called "active" tasks) with index p . Let the "task selection set" $u^d(k)$ be the set of tasks selected for processing by DM d , $d = 1, 2$, at time k . Finally, let the "new arrival set" $a^p(k+1)$ be the set of new arrivals at time $k+1$ with index p . At the next time, the active task sets equal the current task sets plus the new arrival sets minus the task selection sets, with corresponding changes in time available for all tasks. That is,

$$\begin{aligned} S^d(k+1) &= \{(i, j, d) | (i, j+1, d) \in S^d(k) \\ &\cup a^d(k+1) - u^d(k), j \geq 0\}, \quad d = 1, 2, \text{ and} \\ S^c(k+1) &= \{(i, j, c) | (i, j+1, c) \in S^c(k) \\ &\cup a^c(k+1) - u^1(k) - u^2(k), j \geq 0\}. \end{aligned} \quad (1)$$

B. The Resource State

At time k , suppose that DM d allocates $r^d(i_u)$ units of resources to process a selected task (i_u, j, p) . These resources will be tied up for $T_r(i_u)$ units of time before they can be used again. Also, when the other DM, say DM q , transfers $v^d(k)$ units of resources to DM d at time k , these resources will reach DM d after τ units of time delay.

Similar to specifying an active task, a triple (x, l, d) is used to denote x units of DM d 's resources with l units of time-to-go before they can be used. Let $X^d(k) = \{(x, l, d)\}$ be DM d 's "tied-up resource set" at time k . At the next time, the tied-up resources equal the currently tied-up resources plus newly allocated and received resources, with corresponding changes in their tied-up times. That is,

$$\begin{aligned} X^d(k+1) &= \{(x, l, d) | (x, l+1, d) \in X^d(k) \\ &\cup \{(r^d(i), T_r(i), d)\} \cup \{(v^d(k), \tau, d)\}, l \geq 0\}, \\ &d = 1, 2. \end{aligned} \quad (2)$$

Finally, let $R^d(k)$ be the amount of resources owned by DM d at time k , and $r_d(k) = \{r^d(i_u)\}$ be the set of resources allocated at time k . We have the resource ownership dynamics:

$$R^d(k+1) = R^d(k) - v^q(k) + v^d(k), \quad d = 1, 2. \quad (3)$$

The resource usage (tied up units plus newly allocated and transferred units) cannot be greater than the resources that a DM possesses. The following resource availability constraint thus holds for every k :

$$0 \leq \sum_{r^d(k)} r^d(i_u) + \sum_{X^d(k)} x + v^q(k) \leq R^d(k), \quad d = 1, 2. \quad (4)$$

Since (1)–(3) completely describe the task and resource dynamics of the problem, the active task sets $S(k) \equiv [S^1(k), S^2(k), S^c(k)]$, the tied-up resource set $X(k) \equiv [X^1(k), X^2(k)]$, and the resource ownership vector $R(k) \equiv [R^1(k), R^2(k)]$ together form the state of the problem. The task selection set $u(k) \equiv [u^1(k), u^2(k)]$, the resource allocation set $r(k) \equiv [r^d(k), r^d(k)]$, and the resource transfer vector $v(k) \equiv [v^1(k), v^2(k)]$ are the decision variables.

C. Statistics on Task Arrivals and Initial Time Availables

Uncertainties on new task sets $a^p(k)$, $p = 1, 2$, and c are characterized by two independent random processes: one is "task arrival uncertainty," referring to when and which types of tasks will arrive; and the other is "initial time available uncertainty," $T_{ao}(i)$, referring to how long a new task will stay in the opportunity window if left unprocessed. The initial time available uncertainty is assumed, for simplicity, to be uniformly distributed over an appropriate range. The task arrival uncertainty is likely to depend on system states. In Naval Battle Group tactical operations, for instance, new threats often appear in specific patterns based on current threats and enemy's estimate of our resource state. We therefore model the probabilities of new task uncertainties as $p(a^p(k+1)|S(k), R(k), X(k))$ for $p = 1, 2$, and c , i.e., the probability distributions of the new task sets depend on the current state.

D. The Objective Function

DM's strive to maximize the expected team reward in task processing. Two aspects of the reward structure are emphasized: timeliness of processing and accuracy of resource allocation. Timely processing means that when task (i_u, j, p) is selected for processing, its time available should be greater

than or equal to its time required, i.e., $j \geq T_r(i_u)$. Accurate processing means that the amount of resources allocated to task (i_u, j, p) should be equal to the amount of resources required $\hat{r}(i)$. Untimely and/or inaccurate processing result in discounted rewards. The reward for processing task (i_u, j, p) is therefore described by:

$$g(i)g_1(j)g_2(r(i_u)) \quad (5)$$

where $g(i)$ is the value of a type i task, $0 \leq g_1(\cdot) \leq 1$ and $0 \leq g_2(\cdot) \leq 1$ are the timeliness score and accuracy score, respectively, which are user defined. In our model, we have linear discounts for untimely and/or inaccurate processing. That is,

$$g_1(j) \equiv \begin{cases} 1, & \text{if } j \geq T_r(i_u) \\ \frac{j}{T_r(i_u)}, & \text{if } 0 < j < T_r(i_u) \end{cases} \quad (6a)$$

$$g_2(r(i_u)) \equiv \frac{\sum_{m=1}^M r_m(i_u)}{\sum_{m=1}^M \hat{r}_m(i_u)} \quad (6b)$$

subject to $r_m(i_u) \leq \hat{r}_m(i_u)$, where the summation is over all M types of resources.

E. The Markovian Team Decision Problem

Under the previous formulation, the multistage team resource allocation problem over the interval $[0, K]$ can be described as follows:

$$\max_{u(k), r(k), v(k)} E \left[\sum_{k=0}^{K-1} \sum_{u(k)} g(i_u) g_1(j) g_2(r(i_u)) \right] \quad (7)$$

subject to

- 1) the task dynamics (1),
- 2) the resource dynamics (2),
- 3) the resource ownership equation (3), and
- 4) the resource availability constraint (4).

This is a Markovian team decision problem with a stage-wise additive objective function. The optimal resource allocation strategy can be obtained, at least in principle, by stochastic dynamic programming (SDP) [14]. The computation of the optimal (normative) solution, however, is intractable because of the high complexity that results from 1) the need to know the probability distributions of future tasks, 2) the need to plan far into the future and to search in a very large state space, and 3) the need to consider team coordination. In a situation like ours, where an optimal model is intractable, suboptimal models that include salient human limitations and biases (descriptive factors) may provide a judicious starting point to obtain meaningful results. Moreover, if certain descriptive factors are well known *a priori*, they should be included in the model at an early stage. Consequently, instead of solving a "purely" normative model, a preliminary normative-descriptive model is to be solved in the next section as the starting point of our approach.

III. A PRELIMINARY NORMATIVE-DESCRIPTIVE MODEL

A normative-descriptive model can be construed as a constrained optimization, in which human decisions are interpreted as optimal under given cognitive limitations and biases [17]. In the following, a few well-established human limitations and biases are drawn from cognitive and behavioral sciences, and transformed into mathematical representations to form the preliminary normative-descriptive model.

A. Certainty Equivalence

With respect to the need-to-know future probability distributions in the normative approach, Simon [20] noted that "people do not use probability distribution of future events, but content themselves with point predictions (expectations) in making decisions... They somehow make forecasts according to these point predictions, and act upon them in one way or other." This "certainty equivalence" principle is adopted by fixing future probabilities at some typical values (e.g., mean values), and using them as if they were certain (deterministic) in the decision-making process.

As mentioned in Section II, there are two kinds of uncertainties in the model: "task arrival uncertainty" and "initial time available uncertainty." In carrying out the certainty equivalence transformation, the expected initial time available $\bar{T}_{ao}(i)$ is used to replace $T_{ao}(i)$ for each task type. For task arrival uncertainty, the information usually available is the average task arrival rate λ_i , which is the expected number of type i arrivals per unit time. Its inverse $1/\lambda_i$ is the expected interarrival time between two consecutive type i tasks. It is assumed that starting from the current time 0, a type i task will arrive every $\text{Int}(1/\lambda_i)$ units of time, where $\text{Int}(y)$ is the integer floor of y . In other words, a type i task will arrive at future time n if n is a multiple of $\text{Int}(1/\lambda_i)$. The new task sets $a^1(n)$, $a^2(n)$, and $a^c(n)$ are thus replaced by their corresponding certainty ones:

$$\bar{a}^p(n) = \left\{ (i, \bar{T}_{ao}(i)) \mid n = \eta \cdot \text{Int} \left(\frac{1}{\lambda_i} \right), \right. \\ \left. i \in I, 0 < n \leq K, \eta = 1, 2, \dots \right\} \quad (8)$$

where $p = 1, 2, c$. With future arrivals and their initial time availables assumed certain, the stochastic decision problem is reduced to a deterministic one.

B. Myopia and Limited Short-Term Memory

With respect to the need to plan far into the future and to search in a very large state space, the psychology literature tells us that a human is either incapable or unwilling to project the effects of a potential decision far into the future [20]. For each decision, options are generally evaluated based on a short time horizon. Also, because of limited short-term memory, a human can only use a small group of facts to reach a decision [13]. These two facts are captured by replacing the original long time horizon K by a shorter one, K' , and by restraining the number of tasks that a DM can consider in making a decision to be less than or equal to a constant b .

After the simplified problem is solved, only current decisions are implemented. The decisions at the next time will be regenerated in a "moving window" fashion, taking into account new task and resource information. Since K' and b are closely related to system parameters, the values of K' and b will be determined in Section V when all parameters are specified. In Section V we will also explain which b tasks are to be chosen.

C. Team Coordination Myopia

With respect to team coordination, it was observed that team members minimize the need to correctly anticipate uncertain future events, including the coordination activities [24]. This is the team analogy to the single DM's myopia and limited short-term memory. In the problem, team coordination consists of assigning common tasks and transferring resources, and are called task coordination and resource coordination, respectively. Based on the team coordination myopia, it is assumed that a DM prefers task coordination to resource coordination since the latter requires more anticipation on the other DM's future decisions and on future arrivals. It is also assumed that DM's do not consider assigning future common tasks.

D. Self-Centered Resource Ownership

From a normative point of view, a DM should transfer resources to the other DM if the transfer can benefit the team, i.e., increase the total team reward. From psychological and behavioral studies, however, it is known that DM's are more inclined to keep resources rather than to transfer them to other DM's [18]. Combining this with team coordination myopia, we assume that a DM transfers resources only if he/she has extra resources after processing all his/her active tasks within the planning horizon K' ("cover your own needs first").

E. Sequential Coordination and Solution Methodology

Task coordination and resource coordination can be simultaneously considered in a normative approach. This, however, requires a lot of information processing capacities. It has been shown that a human can only do one job at a time if that job requires a lot of information processing capacities. Moreover, it has been pointed out that DM's prefer task coordination to resource coordination. Consequently, it is assumed that a DM first considers task coordination under a given resource state. Resource coordination is used as the last means to improve team performance. This establishes a structure on the decision-making process, and leads to a three-level procedure in solving the team problem: single DM resource allocation, task coordination, and resource coordination.

At the lowest level, we have the single DM resource allocation problem that incorporates certainty equivalence, myopia, and limited short-term memory. With given common task assignments and resource transfers, the problem is formulated as

$$\text{Max}_{u^d(k), r^d(k)} \sum_{k=0}^{K'} \sum_{u^d(k)} g_1(i_u) g_2(j) g_2(r(i_u)) \quad (9)$$

subject to

- 1) the task dynamics (1),
- 2) the resource dynamics (2),
- 3) the resource ownership equation (3), and
- 4) the resource availability constraint (4).

Exploiting special features of the Dream problem, the solution algorithm single decisionmaker resource allocation (Sidra) is a simplified implementation of the forward dynamic programming algorithm presented in [6] and [11].

With Sidra as the core, task coordination is performed with given resource transfers by evaluating different possibilities of common task assignments, and taking the best one. Constrained by self-centered resource ownership and team coordination myopic, resource transfer is determined at the highest level by evaluating different possibilities of resource transfers, and then taking the best one. For details, please see procedure common task coordination (CTC) and procedure resource coordination (RC) in Appendix A.

The solution of the entire problem provides time-by-time decisions on task processing (which tasks, when to process, and the amount of resources), and on coordination (common task assignment and resource transfers). This is a prescriptive model that describes how the team makes decisions at a specific state subject to the above-mentioned human limitations and biases.

IV. EXPERIMENTAL DESIGN

A. Experimental Settings

Driven by the preliminary normative-descriptive model, an experimental paradigm, DREAM, was designed and operationalized to validate the model. The paradigm was implemented on a computer system with two separated workstations, one for each DM. Each workstation consists of a graphic display, an alphanumeric display, and a computer keyboard. The graphic display is an imitation of a radar screen, on which active tasks and their identification numbers are presented. The tasks move at the same constant speed toward the center of the graphic display, and a DM observes the positions of active tasks, resource availability, and current team strength. On a separated alphanumeric display, the task identification number, arrival time, type, resource required, time required, and time available are shown for each active task. No information is given for tasks that have not yet arrived. Using the computer keyboard, a DM processes tasks, communicates formatted messages, and transfers resources. Once a task is processed, the amount of resources allocated to that task is displayed. When the processing finishes or when an unprocessed task reaches the center of the graphic display (penetrates), a performance score (reward) for that task is shown on the alphanumeric display. The graphic display and alphanumeric display are shown in Fig. 1. More detailed descriptions can be found in [10].

In the paradigm, the following simplifications were made to further reduce the cognitive burden of human subjects:

- 1) All types of tasks require the same amount of processing time, i.e., $T_r(i) = T$.
- 2) New tasks arrive in a Poisson stream, and the arrival probabilities of all types of tasks are the same.

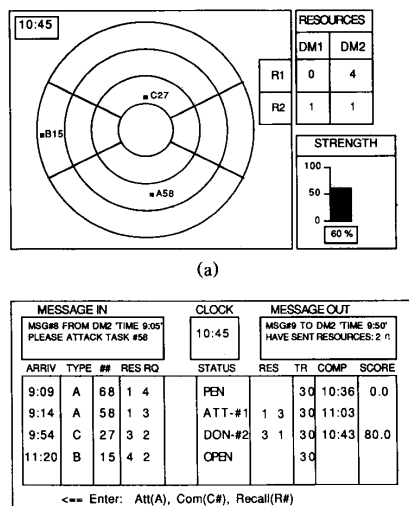


Fig. 1. (a) Graphics display. (b) Alphanumeric display.

3) There are two types of resources, i.e., $M = 2$.

4) Task value equals the sum of its resource required, i.e.,

$$g(i) \equiv r_1(i) + r_2(i). \quad (10)$$

B. Independent Variables

Human decision-making behavior depends on a host of situational variables. In the Dream paradigm, two independent variables are manipulated systematically. The first independent variable is concerned with resource transfer. Three resource transfer conditions are considered: no resource transfer, instantaneous resource transfer, and 15-s delayed transfer. Task arrival rate is the second independent variable. Tasks arrive in a Poisson stream, which is characterized by its arrival rate λ . Three arrival rates of low, medium, and high with $\lambda_l = 1/36$, $\lambda_m = 1/29$, and $\lambda_h = 1/24$ (in the unit of task/s) are considered. A cross combination of a transfer condition and an arrival rate constitutes an investigation condition. Each experimental trial is 13 min in length. In a trial, the DM's encounter ten types of tasks. All types have the same arrival probability and the same expected initial time available of $\bar{T}_{ao} = 122$ s. Among the ten types of tasks, DM1 is responsible for types 1,2,3,4 and DM2 for types 5,6,7,8; they share types 9 and 10. All types of tasks require a processing time $T_r = 30$ s. The resource requirement for each type of tasks is given in Table I. The team has five units of resources of each type. Initially, DM1 owns two units of type 1 resource and three units of type 2 resource, with the remaining belonging to DM2.

C. Measures of Performance

Various measures of performance were recorded during the experiment. Six relevant ones are explained below.

1) *Final Strength (FStr)*: For a task, nonideal processing results in a loss of "team strength," given by $g(i)[1 - g_1g_2]$.

TABLE I
RESOURCE REQUIREMENTS FOR VARIOUS TYPES OF TASKS

TYPE	1	2	3	4	5	6	7	8	9	10
r_1	1	1	2	2	3	3	4	4	2	3
r_2	3	4	3	4	1	2	1	2	3	2

The team strength starts with a fixed value, which equals the total value of tasks in the trial multiplied by 0.4, and is reduced whenever a loss occurs. The final team strength is given as a percentage of the initial strength.

2) *Percentage of Task Processed (%ProT)*: This equals $N_p/N_t \times 100$, where N_p is the number of tasks processed by the team and N_t is the total number of tasks presented in the trial.

3) *Average Accuracy Score (AccS)*: The accuracy score for processing task (i, j, p) is computed according to (6b). The average accuracy score is the average value of accuracy scores for all processed tasks.

4) *Average Timeliness Score (TimS)*: The timeliness score for processing task (i, j, p) is computed according to (6a). The average timeliness score is the average value of timeliness scores for all processed tasks.

5) *Percentage of Common Tasks Processed by DM2 (%Com(DM2))*: This is the percentage of processed common tasks that are processed by DM2.

6) *Resource Transfer Per Task Presented (#Xfr/Task)*: This is the number of resource transfers divided by the number of tasks presented in the trial.

D. Experiment Description

Three teams of two subjects (DM's) each, consisting of undergraduate students at the University of Connecticut, participated in the experiment. The subjects were extensively trained for ten hours on the procedures of the experiment, including transferring resources, processing tasks, etc. The training was performed using statistically equivalent investigation conditions, during which DM's became familiar with workstations, operational procedures, and also developed their own strategies. Prior to performing a trial, the two DM's were allowed to discuss their strategies between themselves. Once the trial started, the two DM's were physically separated. Communications between DM's were performed via the alphanumeric terminals using formatted messages. A DM could send an instantaneous message stating his intention to process or not to process a particular common task, and to request his partner to process or not to process a particular common task. He could also request or inform the sending of specific amount of resources. Resource transfers, however, might be subject to time delays, as mentioned previously.

V. MODEL VALIDATION

A simulation shell for the Dream paradigm was developed by Hsu [7] to test the solution methodology developed. At each time (in the unit of a second), the shell generates and

TABLE II
EXPERIMENTAL AND MODEL RESULTS: LOW ARRIVAL RATE

Delay		FStr	%ProT	AccS	Tims	%Com(DM2)	#Xfr/Task
∞	Exp.	74.4(3.7)	99.2(0.8)	92.4(0.5)	97.9(1.4)	66.7(8.0)	NA
	Model	82.3	100.	93.1	100.0	71.4	NA
0	Exp.	81.7(4.0)	95.4(2.0)	95.6(0.9)	96.3(1.9)	80.6(7.0)	0.43(0.04)
	Model	86.5	100.	97.4	97.1	71.4	0.36
15	Exp.	84.6(2.1)	97.7(1.0)	94.5(0.8)	99.1(0.6)	80.9(6.0)	0.20(0.06)
	Model	85.4	100.	94.7	99.4	71.4	0.32

TABLE III
EXPERIMENTAL RESULTS: MEDIUM ARRIVAL RATE

Delay		FStr	%ProT	AccS	TimS	%Com(DM2)	#Xfr/Task
0	Exp.	57.9(10.3)	86.4(2.5)	93.0(1.6)	91.0(3.7)	68.4(12.4)	0.37(0.06)
	Model	61.2	96.3	85.3	98.0	55.5	0.26
15	Exp.	64.3(11.0)	86.4(3.3)	92.4(0.5)	95.5(2.5)	72.2(7.7)	0.31(0.04)
	Model	69.5	92.6	89.6	96.7	22.2	0.19

TABLE IV
EXPERIMENTAL RESULTS: HIGH ARRIVAL RATE

Delay		FStr	%ProT	AccS	TimS	%Com(DM2)	#Xfr/Task
0	Exp.	64.4(6.6)	88.9(2.2)	91.7(2.0)	94.5(1.4)	61.3(5.8)	0.33(0.07)
	Model	70.4	90.9	90.1	98.0	36.4	0.24
15	Exp.	66.3(5.4)	91.4(2.7)	89.5(1.9)	95.2(0.6)	64.7(3.1)	0.14(0.05)
	Model	74.2	93.9	90.1	99.4	54.5	0.12

presents to the normative-descriptive model the same set of tasks as those presented to human DM's in the trial. After the model makes decisions, the shell implements them and records corresponding performance measures. The application of our model to various investigation conditions is straightforward once we specify the undefined parameters in the model, i.e., the time horizon K' and the size of the constrained task set b .

A. Model Parameters

The factors that determine how a task will be processed include the task's time available, its resource required, and the resource availability of the DM. We roughly count them as three chunks of information, and assume that a DM considers two tasks at a time. This yields roughly six chunks of information in the short-term memory, the supposed size of human short-term memory [13]. Since all types of tasks have the same processing time requirement, and task value equals the sum of its resource requirements, the tasks have the same value per unit resource and per unit processing time. All tasks are thus worth roughly the same level of consideration, and a DM is assumed to choose the two tasks with the shortest time available, i.e., the two most "urgent" ones.

In the experiments, the average human delay is 11 s per operation. This is the average time for a subject to type in a decision through the computer keyboard. To include this factor, each model decision is delayed by 11 s. The time horizon K' is chosen to be $1/\lambda_m + T_p$, by assuming that each DM only looks ahead to process one more task, where $1/\lambda_m$ is the medium interarrival time of the experiment. This results in $K' = 70$ s, with one second as the basic time unit.

B. Experimental and Model Results

Experimental and model results are summarized in Tables II-IV. For the condition with no resource transfer, experiments were implemented for the low arrival rate only. For the medium arrival rate, each investigation condition was run once on the three teams. All other investigation conditions were repeated twice on the three teams. Experimental data are presented with their sample means and standard errors. *The model predictions on average team performances are obtained with the same set of parameters throughout all investigation conditions.* This is an important characteristic of predictive models that employ a goal-oriented construct; model parameters do not have to be retuned for each change in an independent variable.

Fig. 2 compares model and experimental results graphically for the conditions with instantaneous resource transfers. Note that the model generates good predictions on the final team strength, and also matches other performance measures quite well. In fact, most model predictions fall within two standard errors of experimental results.

C. Additional Cognitive Limitations

Comparing experimental results and model predictions shows a notable pattern across all investigation conditions. This pattern involves percentage of tasks processed; the model always achieves better scores. The model also obtains better timeliness scores, whereas subjects have better accuracy scores for most conditions with high arrival rate and long transfer delay. Furthermore, as task arrival rate increases, subjects may fail to process a task, while the model still processes it with smaller amount of resources. These can be seen from Fig. 2(b)-(d). We conclude that subjects have a

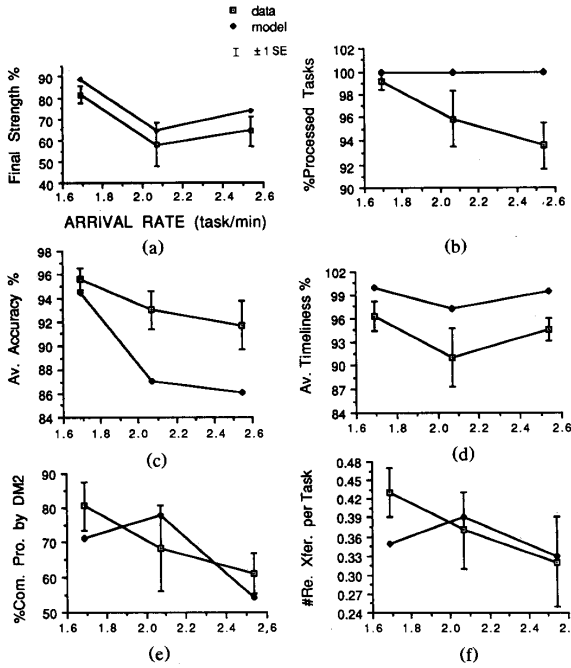


Fig. 2. Model versus experimental results (instantaneous resource transfer). (Model parameter: time horizon = 70, size of certainty equivalent task set = 2.)

TABLE V
REVISED MODEL RESULTS: LOW ARRIVAL RATE

Delay	FStr	%ProT	AccS	TimS	%Com(DM2)	#Xfr/Task
∞	82.3	100.	93.1	100.0	71.4	NA
0	86.5	100.	97.4	97.1	71.4	0.36
15	85.4	100.	94.7	99.4	71.4	0.32

TABLE VI
REVISED MODEL RESULTS: MEDIUM ARRIVAL RATE

Delay	FStr	%ProT	AccS	TimS	%Com(DM2)	#Xfr/Task
0	61.6	88.9	93.6	97.5	55.5	0.33
15	66.7	85.2	94.0	94.6	50.0	0.22

TABLE VII
REVISED MODEL RESULTS: HIGH ARRIVAL RATE

Delay	FStr	%ProT	AccS	TimS	%Com(DM2)	#Xfr/Task
0	73.1	90.9	93.6	98.7	54.5	0.15
15	68.6	90.9	92.2	97.2	50.0	0.12

tendency to ignore a task if they cannot allocate sufficient resource to it. Such a pattern can be interpreted as a “filtration strategy” (eliminating actions on some tasks, or elimination by aspect (EBA)) suggested by Tversky ([22], [16]). To incorporate this human bias into the model, we assume that a DM ignores a task unless he/she can achieve more than 60% of its accuracy score.

By adding the above bias into the model, we obtain final model results as shown in Tables V–VII. Fig. 3 compares

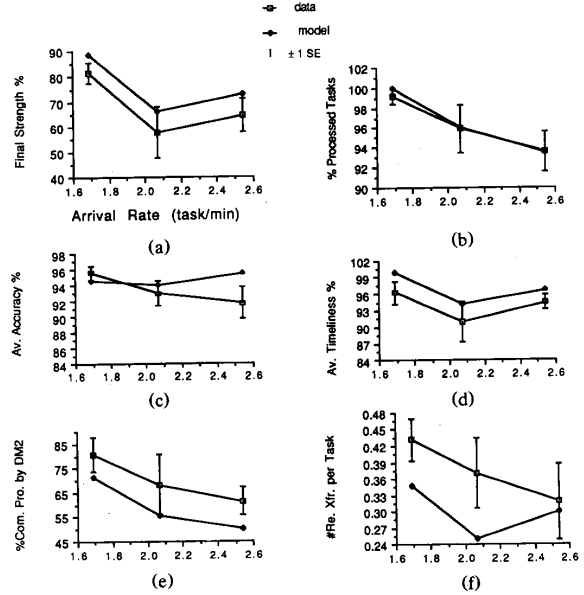


Fig. 3. Normative-descriptive model versus experimental results (instantaneous resource transfer). (Model parameters: time horizon = 70, size of certainty equivalent task = 2; give up a task unless 60% of its accuracy score is achievable.)

model and experimental results graphically for the conditions with instantaneous resource transfers. Now, among all 41 measures, 18 (43.9%) fall within one standard error, 30 (73.2%) within two standard errors, and 38 (92.7%) within three standard errors. Only three (7.3%) are out of three standard error regions. Note that model and experimental results match well not only in range but also in pattern.

D. Discussions

Observing how a normative formulation is altered to describe human behavior yields insights to the human decision-making process. For example, data-model comparison suggests that humans prefer to concentrate on doing good jobs on selected tasks and ignore the processing of others. As a result, the filtration strategy is introduced into the team decision-making strategy. Notice how the measures percentage of tasks processed and average accuracy score change from Figs. 2 to 3. This shows that DM’s do adapt to higher workload by “filtering” those tasks that they cannot accurately process. Furthermore, identifying human perceptual and cognitive processes helps us understand the effects of various biases, heuristics, and other inherent limitations of human DM’s. The model can suggest ways to improve human performance by alleviating these limitations and biases. For example, when we relax the number of tasks that a DM can consider at one time, increase the planning horizon, or make resource coordination strategy less self-centered and less myopic, the model is able to achieve better final strength for almost all the cases. This suggests that team performance can be further improved through decision aiding and more training. The above insights may not necessarily be obtainable through a purely experimental approach.

VI. SUMMARY

A major task in studying distributed resource allocation in teams is to develop a mathematical formulation that captures key ingredients, and is still subject to systematic analysis. Another task is to explain human behavior as exhibited in real decision-making environments. In this paper, the distributed resource allocation problem was first formulated as a stochastic Markovian decision model. The huge computational requirements make the finding of the optimal solution unrealistic. Moreover, it is known that a purely normative approach does not reflect actual human performance. A preliminary normative-descriptive model was thus constructed by blending the normative model with well-known human cognitive limitations and biases. The model was solved by using a constrained optimization technique that is intuitively compatible with the human decision-making process. The effects of human limitations and biases are mimicked in the solution procedures. Driven by the model, the Dream paradigm was designed and operationalized, and a sequence of human experiments were performed under different investigation conditions. A new cognitive bias was then identified to explain the differences between the preliminary model predictions and experimental data, and was incorporated into the model. The final normative-descriptive model results match human team behavior in almost all measures. The model thus provides a tool to describe human performance within the constrained environment, and gives us insights to the team decision-making process.

APPENDIX A

Procedure: Sidra

- 1) [Initialize resource state and task state.]
 - 1.1) For a given resource state and resource transfer sequence, use Equations (2) and (3) to form an $M \times K'$ "Resource Availability Matrix" Y^d so that its k th column Y_k^d is the resource available to DM d at time k .
 - 1.2) Construct a "Certainty Equivalent Task Set" $\bar{S}^d(0)$ consisting of the b most urgent active and "pseudo-" active tasks. A pseudo-active task is a certainty equivalent future task with its time available equal its certainty equivalent arrival time plus its expected initial time available.
 - 1.3) Arrange the tasks in the ascending order of their time availables.
- 2) [Find the amount of resources to allocate.]
 - 2.1) Select the task with the shortest time available.
 - 2.2) Check resource availability Y_k^d at each time k so as to find the latest time when the task can be processed to yield the largest reward.
 - 2.3) Update Y^d according to the resulting resource allocation.
 - 2.4) Remove the task from $\bar{S}^d(0)$ and go back to Step 2.1 until $\bar{S}^d(0)$ is empty.
- 3) [Determine the time to process.]

Process tasks in the order of their ascending time availables and at their earliest possible time without violating resource availability constraints.

Procedure: CTC (Common Task Coordination of DM d)

- 1) [Form the certainty equivalent task sets S .] Form Certainty Equivalent Task Sets $\bar{S}^d(0)$ and $\bar{S}^q(0)$ in the absence of common tasks according to Step 1.2.
- 2) [Select a common task.] Find the most urgent active common task.
- 3) [Determine who should process the task.]
 - 3.1) If there are fewer than b tasks in $\bar{S}^d(0)$, temporarily add the common task to $\bar{S}^d(0)$. Otherwise, if the common task has a shorter time available than that of a task already in $\bar{S}^d(0)$, temporarily substitute the longer time available task by the common task. Use the algorithm Sidra to find the team reward by assigning the common task to DM d .
 - 3.2) Repeat (3.1) by changing DM d to DM q .
 - 3.3) Compare the team rewards resulted from (3.1) and (3.2), and determine the DM who can bring a larger increase in team reward.
- 4) [Implement task coordination.]
 - 4.1) If the DM determined in Step 3 is DM d , include the task in the set $\bar{S}^d(0)$ and send the message "I will process task #" to DM q if this has not been done yet.
 - 4.2) Otherwise, send the message "Please process task #" if this has not been done yet.
 - 4.3) Remove the task from the set $S^c(0)$, and go back to Step 2 until the set $S^c(0)$ is empty.

Procedure: RC (Resource Coordination of DM d)

- 1) [Find the decisions without transfers.] Without resource transfers, find the initial task processing plan.
- 2) [Select the task requiring resource transfer.] Find the most urgent active task among all partially processed or unprocessed ones in the team's initial task processing plan. If no such task exists, exit. Otherwise, go to step 3.
- 3) [Determine who needs additional resources and the amount.] Find the amount of resources needed for accurately processing the task and the corresponding DM. Let the DM be DM d .
- 4) [Determine when to transfer.] Subject to DM q 's initial task processing plan, find the earliest time when he will have at least one unit of resource to transfer. Let that time be n_t .
- 5) [Determine the amount of resources to transfer.] Subject to DM q 's initial task processing plan, let $v^d(n_t)$ be the largest amount of resources that DM q can transfer at time n_t .
- 6) [Evaluate the consequence of the transfer.] After incorporating the resource transfer $v^d(n_t)$, use procedure SIDRA to solve DM d 's problem.
- 7) [Decide whether to realize the transfer.] If there is no increase in team reward through the resource transfer, exit without changing the initial task processing plan. Otherwise, go to step 8.
- 8) [Implement the resource transfer.] DM d requests v^d units of resources from DM q if this has not been done yet. DM q transfers v^d units of resources to DM d if n_t is the current time.

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REFERENCES

- [1] K. R. Baker, *Introduction to Sequencing and Scheduling*. New York: Wiley, 1974.
- [2] L. G. Bushnell, "Dynamic information processing in a team," Electrical and System Engineering Dep., Univ. Connecticut, Masters thesis, 1987.
- [3] E. G. Coffman, *Computer and Job Shop Scheduling*. New York: Wiley, 1976.
- [4] M. D. Diamond and O. M. Carducci, "Decision processes for large scale resource allocation problems," in *Proc. 8th MIT/ONR Workshop on C3 Systems*, June 1985, Cambridge, MA, pp. 153-160.
- [5] E. E. Entin, D. Serfaty, R. M. James, J. G. Wohl, and J. C. Derkert, "Experiment validation of an anti-submarine warfare commander situation assessment model," Alphatech, Inc., Burlington, MA, tech. rep. 307, 1987.
- [6] E. Horowitz and S. Sanhi, *Fundamentals of Computer Algorithms*. Rockville, MD: Computer Science Press, 1978.
- [7] J. Y. Hsu and D. Serfaty, "An introduction to the distributed resource allocation and management simulation shell (DREAMSS), Alphatech, Inc., Burlington, MA, tech. mem. 241, 1987.
- [8] I. L. Janis, *Decision Making*. New York: Free Press, 1977.
- [9] D. L. Kleinman, "Solving the optimal attention allocation problem in manual control," *IEEE Trans. Automat. Contr.*, vol. AC-21, pp. 813-822, Dec. 1976.
- [10] C. Kohn, D. L. Kleinman, and D. Serfaty, "Distributed resource allocation in a team," in *Proc. 1987 Command and Control Research Symp.*, July 1987, pp. 221-233.
- [11] R. E. Larson and J. L. Casti, *Principles of Dynamic Programming, Part I*. New York: Marcel Dekker, 1978.
- [12] E. L. Lawler, J. K. Lenstra, and A. H. G. Rinnooy Kan, "Recent developments in deterministic sequencing and scheduling: A survey," in *Deterministic and Stochastic Scheduling*, M. A. H. Empster, J. K. Lenstra, A. H. G. Rinnooy Kan, eds. Boston: D. Reidel, 1982.
- [13] P. H. Lindsay and D. A. Norman, *Human Information Processing*. London: Academic, 1977.
- [14] P. B. Luh, X. Y. Miao, S. C. Chang, and D. A. Castañon, "Stochastic task selection and renewable resource allocation," *IEEE Trans. Automat. Contr.*, vol. 34, pp. 335-339, Mar. 1989.
- [15] K. R. Pattipati, D. L. Kleinman, and A. R. Ephrath, "A dynamic decision model of human task selection performance," *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-10, pp. 217-231, May 1983.
- [16] J. W. Payne, J. R. Bettman, and E. J. Johnson, "Adaptive strategy selection in decision making," Duke University, Durham, NC, rep. 86-1, 1986.
- [17] A. Rapoport, "Research paradigm for studying dynamic decision behavior," in *Utility, Probability, and Human Decision Making*, D. Wendt and C. Vlek, eds. Dordrecht, Holland: Reidel, 1975, pp. 349-369.
- [18] T. B. Roby, *Small Group Performance*. Skokie, IL: Rand McNally, 1968.
- [19] M. K. Schaefer, "Optimal allocation of recoverable items," *Decision Science*, pp. 147-155, 1982.
- [20] H. A. Simon, *Models of Bounded Rationality: Behavioral Economics and Business Organization*. Cambridge, MA: MIT Press, 1982.
- [21] L. Sjöberg, T. Tyszka, and J. A. Wise, Eds., *Human Decision Making*. Doxa AB, Sweden, 1983.
- [22] A. Tversky, "Elimination by aspects: A theory of choice," *Psychological Review*, vol. 79, 1972, pp. 281-289.
- [23] Z. J. Wu, P. B. Luh, S. C. Chang, and D. A. Castañon, "Optimal task allocation for team of two decision makers with

- three classes of impatient tasks," *IEEE Trans. Automat. Contr.*, vol. 33, pp. 42-49, Jan. 1988.
- [24] P. Yetton and P. Bottger, "The relationships among group size, member ability, social decision schemes, and performance," *Organizational Behavior and Human Performance*, vol. 37, 1983, pp. 145-149.



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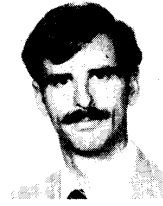
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