A Normative–Descriptive Approach to Hierarchical Team Resource Allocation

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***Abstract*—Dynamic, distributed, human team resource allocation and task processing is considered in an abstracted Navy-like command and control environment. A hierarchical team of one leader and three subordinates is to process multiple types of randomly arriving tasks (threats) that have different processing resource requirements, time requirements, values, and deadlines. Possessing a limited amount of renewable and transferable resources, each subordinate is responsible for processing a subset of these tasks. Since subordinates may have tasks of different values and resource requirements, dynamic resource transfer/coordination is needed to maximize the team's performance. Two kinds of team leader (resource coordinator) are considered. An active leader transfers resources among the subordinates, and the subordinates are responsible for task processing. A passive leader, on the other hand, provides off-line guidance only and does not participate in on-line resource coordination. The objective of this research is to describe, and analytically model, the individual decision making and coordination processes of both the active-leader team and the passive-leader team. As a first step, distributed normative models of the team decision-making problem are formulated. Driven by the models, a team-in-the-loop experiment is designed and operationalized to verify experimental hypotheses and to provide data to compare with model predictions. The "self-centered" bias (wherein human decision makers overvalue their own responsibilities) is identified as a major contributor to model–data mismatch. Incorporating such human cognitive limitations and biases into the normative models, the resulting normative–descriptive models successfully replicate experimental results, and provide insight to team decision-making processes.**

I. Introduction

A. Problem Context

The problem of team resource allocation and task processing arises in many different situations, e.g., military Command and Control (C2), electric power distribution, air-traffic control, and product distribution and supply [1], [3], [5], [11], [13]–[15]). The motivation for the research in this paper comes from naval battle group tactical operations which involve resource allocation and task processing performed by a hierarchical team of human decision makers (DM's).

Fig. 1 shows a typical naval battle group command structure consisting of a composite warfare commander (CWC) and three functional commanders: an anti-air warfare commander (AAWC), an antisubmarine warfare commander (ASWC), and an antisurface warfare commander (ASuWC). The AAWC is responsible for prosecuting air threats, the ASWC submarine threats, etc. Each functional commander owns a certain amount of resources (fixed-wing aircraft, helicopter, etc.) with which to process his randomly arriving tasks (enemy airplanes, ships, or submarines). These tasks have different priorities, and may require different amount of resources and time for their processing. Some tasks may require resources from other functional commanders, and are referred to as "joint" tasks. Those tasks that do not require resources from other functional commanders are called "individual" tasks. The CWC may direct or supervise the resource coordination necessary to process joint tasks. If a task is not processed within a specified time period (opportunity window) the team will incur some loss/damage. Consequently, the team must dynamically coordinate its resources among three functional commanders for task processing to minimize the total loss.

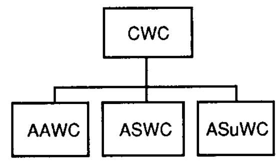

Fig. 1. Naval battle group command structure.

B. Approaches to Study Team Decision Making

Team coordination and decision making have been studied by economists, organization theorists, psychologists, applied mathematicians, and systems engineers using three different approaches. The first approach formulates a pure mathematical optimization problem, in which a DM with unlimited computation capability is assumed to make decisions by maximizing a well-defined reward function (e.g., [3], [6], [8], [10], [12], [15], [21], [22]). For the hierarchical team problem, details of normative models and solution methodologies are provided in [3], [12], [21], and [22]. The shortcoming of this approach, as Herbert Simon states, is that human DM's simply do not have the "wits to maximize" [19]. The approach may tell how people ought to act, but not how they actually act.

The second approach studies the problem empirically in a well defined and controlled context. By gathering large amount of data and analyzing it, a model can be constructed to fit the data (e.g., [1], [2], [4], [7], [9], [18], [19], [23]). For the hierarchical team problem, some empirical results on

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how people act are presented in [1] and [2], and how human decisions are biased are reported in [5], [7], [9], [18], and [23]. Without establishing a baseline, however, conclusions from an empirical study are often vague and nonextensible. Moreover, the empirical approach does not have predictive capability for situations where there is not directly applicable data. Such a capability is clearly needed for system design.

In recent years, the normative–descriptive approach has emerged as a middle ground alternative for studying human team decision making (e.g., [14], [16], [20], [24]. The basic tenet of this approach is that motivated expert DM's strive for optimality, but are constrained from achieving it by their inherent limitations and biases. The normative–descriptive approach therefore constrains the normative solution by empirically determined cognitive characteristics, and aims to provide realistic predictions of human performance. It thus brings together how people act and how we believe that they ought to act, and is the approach followed in this paper.

It may be worth noting that the apparent disorderliness in many decision-making environments has led some people to argue that there is little order in organizational decision making. The "garbage can model" of organizational decision making assumes that problems, solutions, decision makers and choice opportunities are independent, exogenous streams flowing through a system [11]. In other words, problems, solutions, and participants are joined together more by the timing of their arrivals than by other attributes. We do not agree with this view, and feel that human decision processes can be modeled, causally and analytically.

For distributed team resource allocation and task processing problems, the normative–descriptive approach has demonstrated an ability to quantify human decision-making processes in several limited but significant contexts. Normative–descriptive models have been developed for a two-person parallel team (a team without a leader [14], and a three-person parallel team [20]. Both models, however, assumed that each DM has global information, solves the same global problem, but only implements his part of the solution—i.e., a centralized solution process with a decentralized implementation. These types of models, however, cannot be used directly to predict individual decision making within a team nor to represent the team's coordination process as coordination is, per force, "perfect" in a centralized model.

C. Overview of Paper

To understand what a leader brings to a team and to connect this study with our previous work on parallel teams, this paper compares two extreme types of hierarchical teams: an active-leader team and a passive-leader team. In an active-leader team, the leader (i.e., resource coordinator) assumes full responsibility for resource coordination by actually transferring resources among subordinates and announcing his plans for future resource transfer(s). In a passive-leader team, on the other hand, the leader is involved in off-line guidance but not in on-line coordination. Here, the subordinates coordinate their own resources.

The remainder of this paper is organized as follows. In Section II, a task processing submodel and a resource coordination submodel are developed by decomposing the overall team decision-making processes. These two submodels are then used to describe the individual decision-making and coordination processes of each team member (including the leader and the subordinates) for both the active-leader team and the passive-leader team. Driven by the modeling context, a team-in-the-loop experiment is designed and run across three independent variables: two levels of leader's involvement, two levels of tempo, and three levels of external coordination incentive. The experimental design and hypotheses are presented in Section III. The experimental results are presented in Section IV. In Section V human data and model results are compared, and the "self-centered" bias (wherein a DM over-values his own responsibilities) is identified for both the leader and subordinates as a major contributor to model-data mismatch. Incorporating this bias and others into the normative models, the resulting normative–descriptive models successfully replicate experimental results, and provide insights to the team decision making and coordination processes. Concluding remarks are given in Section VI.

II. Normative Models

In this section a hierarchical team resource allocation model is formulated that captures the essence of the naval team problem discussed previously. The overall model consists of two submodels. At the first level, a task processing submodel is developed to predict each team member's "optimal" decision making. The second level consists of a resource coordination submodel to predict the intrateam resource exchanges.

A. Mathematical Problem Formulation

Consider a hierarchical team of three subordinate decision makers (DM1, DM2, DM3) one leader (DM0). Any particular subordinate DMp, $p1, 2, 3$, is responsible for processing a mix of I^p types of randomly arriving tasks. Each task of type i^p, $1 \cdots i^p\ I^p$, has a processing time requirement $T(i^p)$, an initial time available $t_0(i^p)$ (the difference between a task's arrival time and its deadline), a value $v(i^p)$, and a resource requirement vector $(i^p) = [r1, r2, r3]$, where $r1$ denotes the amount of type 1 resource required, etc. A task must be processed before its deadline, or else the team will suffer a loss of $v(i^p)$. Equivalently, if a task is processed before its deadline with the required amount of resources, the task value can be considered as a reward to the team. Allocation of less than the required resources will result in a partial reward.

The three types of resources that the team owns are renewable, i.e., any resources allocated to a task are available for reuse once the task processing is complete. For simplicity, it is assumed that only type p resource is needed by DMp to process his "individual" tasks, those tasks that require only one type of resource. It is clear that if all tasks were of the individual type, DM1 should just own type 1 resource, etc. A subordinate, however, must also process "joint" tasks that require all three types of resource. These tasks are thus the driving force for dynamic resource coordination (resource transfers) within the team.

For simplicity, it is assumed that the information structure is centralized, i.e., all DM's have the same global information regarding current tasks and resources. It is also assumed that a subordinate can only process one task at a time, and cannot start a new processing before the previous one is completed. To process a task, some resources must be allocated to it. Once allocated, these resources will be tied-up for a time $T(i^p)$ until the processing is completed. The allocation of a resource to a task thus forecloses the use of that resource by the team for some period of time. The hierarchical team resource allocation and task processing problem is therefore to determine who should process which task with how many units of resources at what time, and who should transfer which units of resources to whom at what time so as to maximize the team reward over a finite time period. The first part of the problem is concerned with task processing, and the second part is concerned with resource coordination. Discrete-time models for these two parts developed below.

B. Task Processing Submodel

The task processing submodel for subordinate DMp is formulated within a dynamic programming framework by developing task and resource dynamical equations, and presenting a suitable objective function (for the team) to maximize.

Task Dynamics: At time k, let $(i^p,\ j_k)$ be a type i^p task with $j_k > 0$ units of time remaining before it reaches its deadline. Denote $S^p(k) = \{(i^p, j_k)\}$ as the set of arrived and yet unprocessed tasks (the so-called "active task set"), $u^p(k) = (i_u^p, j_k)$ as the task selected for processing at time k, and $a^p(k+1) = \{(i^p, t_0(i^p)\}$ as the set of new arrivals at $k+1$. At the next time instant, the active task set for DMp will contain his currently active tasks plus new arrivals minus the selected task, with corresponding changes in time available for all tasks. DMp's task dynamics is thus described by

$$S^p(k+1) \equiv \{(i_p, j_k - 1) | (i_p, j_k) \in S^p(k) \cup a^p(k+1) - u^p(k), j_k > 1\}. \tag{1}$$

Resource Dynamics: The dynamics of the resources owned by DMp are driven by his task processing decisions and also by the team's resource transfers. At time k, let $z_q^p(k) \in \{1,2,3\}, p \neq q)$ be the amount of resources transferred from DMq to DMp. Define $\mu^p(k) \equiv \sum_{p \neq q} z_p^q(k)$ as the amount of resources that DMp sends out at time k, and $\nu^p(k) \equiv \sum_{q \neq p} z_q^p(k)$ as the amount of resources that are sent to DMp at time k. It can be shown that for a three-subordinate team $\{z_q^p(k)\}$ and $\{\mu^p(k), \nu^p(k)\}$ are equivalent representations and can be uniquely determined from each other. For notational simplicity, $\{\nu^p(k), \nu^p(k)\}$ is used to denote the team's resource transfer variables. A "resource transfer plan" for DMp over the time window $[k, k+K]$ is denoted as:

$$[\mu^p(k), \nu^p(k)]_K \equiv [\{\mu^p(k), \nu^p(k)\}, \cdots, \{\mu^p(k+K-1), \nu^p(k+K-1)\}]. \tag{2}$$

At time k, let $r(i_u^p)$ be the amount of resources allocated to the selected task. These resources will be tied-up for $T(i_u^p)$ units of time (time required for the selected task) until the processing is finished. Also, a resource transfer takes t units of time to complete. Let $(x^p,\ m_k)$ denote DMp's x^p units of resources with mk units of "time-to-return" at time k, where x^p is a three-dimensional vector and m_k is the amount of time before x^p can be reused. Denote $X^p(k) = (x^p(k), m_k)$ as DMp's "tied-up resource set." The resource dynamics that result from task processing and resource transfer can then be modeled in a way analogous to the task dynamics. At the next time, $Xp(k+1)$ will include the currently tied-up resources plus resources newly allocated or transferred from other subordinates, with corresponding changes in time-to-return. The resource dynamics is thus described by

$$X^p(k+1) \equiv \{(x^p, m_k - 1) | (x^p, m_k) \in X^p(k) \cup (r(i_u^p), T(i_u^p)) \cup (\nu^p(k), \tau), m_k > 1\}. \tag{3}$$

Let $R^p(k)$ be the total amount of resources owned by DMp at time k. The dynamics of this resource ownership are described by

$$R^p(k+1) = R^p(k) - \mu^p(k) + \nu^p(k). \tag{4}$$

Finally, the resource availability constraint states that DMp cannot use more resources than those that are currently available to him, i.e.,

$$r(i_u^p) \leq R^p(k) - \mu^p(k) + \nu^p(k). \tag{5}$$

The Task Processing Problem: If task (i_u^p, j_k) is processed with units of resources at time k and the processing can be completed before the task's deadline, the team will receive a reward $g[u^p(k), r^p(k)] = v(i_u^p) g_1[r(i_u^p)]$, where the resource "accuracy" score $g_1[r(i_u^p)]$ is defined by

$$g_1[r(i_u^p)] = \left(\frac{\sum_{l=1}^{3} r_l(i_u^p)}{\sum_{l=1}^{3} \bar{r}_l(i_u^p)} \right)^2. \tag{6a}$$

Equivalently, we can say that the team will have a loss of

$$L[u^p(k), r^p(k)] = v(i_u^p)\{1.0 - g_1[r(i_u^p)]\} = v(i_u^p) - g[u^p(k), r^p(k)]. \tag{6b}$$

It is assumed that $r_l(i_u^p) \leq \bar{r}_l(i_u^p)$, i.e., allocating more than the required amount of any type of resource is not allowed. This constraint also assures that different resource types will not trade-off against each other in (6a) In DMp's task processing submodel, it is assumed that the team resource transfer plan is given. Since the subordinates interact only through resource coordination, and since the team reward is the sum of individual rewards, maximizing the team reward is equivalent to maximizing the individual rewards separately. With a given resource transfer plan $[(\mu^p(\bullet), \nu^p(\bullet)]K$ and probability distribution of new arrivals $a^p(\bullet)$, DMp's task processing problem is to maximize the expected individual reward by selecting tasks and allocating resources $[u^p(\bullet), r^p(\bullet)]$ over the planning horizon K. His task processing problem is thus formulated as

$$\max_{u^p(\bullet), r^p(\bullet)} \left[\mathrm{E}_{a^p(\bullet)} \sum_{n=k}^{K-1} g[u^p(n), (r^p(n))] \right] \tag{7}$$

subject to the system dynamics (1), (3), (4) and the resource availability constraint (5). Let $J^{p*}(\mu^p(\bullet), \nu^p(\bullet))$ be the optimal expected reward of DMp for the given resource transfer plan $[\mu^p(\bullet), \nu^p(\bullet)]K$.

C. Resource Coordination Submodel

The resource coordination problem is to determine the team resource transfer plan so as to maximize the overall team reward, i.e.,

$$\max_{[\mu^p(\bullet), \nu^p(\bullet)]_K} \sum_{p=1}^{3} J^{p*}(\mu^p(\bullet), \nu^p(\bullet)). \tag{8}$$

This resource coordination problem can, in principle, be conceived of as a two-level optimization problem. For a given resource transfer plan $[\mu^p(\bullet), \nu^p(\bullet)]_K$, the low-level computes $J^{p*}(\mu^p(\bullet), \nu^p(\bullet)), p = 1, 2, 3$. The high-level then optimizes the team resource transfer plan based on low-level results. However, it does not make much sense to determine $J^{p*}(\mu^p(\bullet), \nu^p(\bullet))$ by using the exact task processing model (7). If a DM is able to solve the entire team problem completely and optimally, there would be little need for distributed decision making.

In our approach, the resource coordination submodel is aggregated across both task and time dimensions. This is consistent with the common practice that coordination in an organization is often considered in less detail and also at a larger time scale than other problems. Specifically, each subordinate's performance $J^{p*}(\mu^p(\bullet), \nu^p(\bullet))$ is estimated within the resource coordination submodel through an aggregated task processing submodel, in which both task and time aggregations are performed. In task aggregation, differences among various types of individual tasks are ignored. Each individual task is replaced by a "generic" individual task, having the averaged resource requirement, time requirement, initial time available and value of all individual tasks. A similar approach is followed for joint tasks. This aggregation enables DM's to focus more on the choice between individual tasks versus joint tasks, rather than on the different strategies within individual or joint task processings. In time aggregation, the decisions are restricted to time instances $k, k+\eta, \cdots, k+n\eta, \cdots, k+N\eta$ for some integer $h > 1$ and N=Integer(K/η). This reduces the decisions of resource transfer and task processing to a few time instances, the so-called "decision epochs." The resulting aggregated task processing submodel is similar to the original task processing submodel (7), and is omitted for the conciseness of the paper. Based on the aggregated task processing submodel, the resource coordination submodel is to select an aggregated resource transfer plan

$$\begin{aligned}&[\mu^p(k), \nu^p(k)]_N \\ &\equiv [(\mu^p(k), \nu^p(k)), \cdots, (\mu^p(k+N\eta), \nu^p(k+N\eta))]\end{aligned} \tag{9}$$

for each subordinate p so as to maximize the overall team reward following (8).

D. Solution Methodology

The task processing submodel can, in principle, be solved via dynamic programming. The resource coordination submodel requires the resolution of three aggregated task processing subproblems and a parameter optimization problem over N steps, where N=Integer(K/η). When K is large, the optimal solutions of these two submodels are intractable. It is well known that humans do not have the cognitive capability to solve these problems optimally [16], [19]. Our previous efforts in modeling human decision making have also shown that it is advantageous to incorporate some well known human cognitive limitations into the models at an early stage. The resulting models can be more readily solved to provide a starting point for the development of normative–descriptive models [15], [20]. In the following, two simplifications are made in the normative models. The first one assumes that humans can only consider resource coordination over a limited horizon at a time. The second assumes that humans evaluate effects of future decisions less precisely than those of current ones.

Specifically, it is assumed that a team considers resource coordination over a short horizon $L \ll N$, or $L\eta \ll K$. Beyond $L\eta$, the resource ownership of subordinates is assumed to remain unchanged. The team's resource transfer plan within the short coordination horizon $L\eta$ is denoted as $[(\mu^*(\bullet), \nu^*(\bullet)]_L$ to emphasize that resource transfers are planned only at decision epochs. This limited coordination horizon is then exploited to decompose the task processing submodel into two time intervals: one within the coordination horizon $L\eta$, and the other beyond the coordination horizon.

Without resource transfers, the task processing problem of each subordinate beyond $L\eta$ is decoupled from those of the others, and can be treated separately. Furthermore, since a subordinate can only process one task at a time and there is no resource transfer beyond $L\eta$, a subordinate would allocate the maximum allowable amount of resources to each task. Specifically, if DMp owned R^p amount of resources beyond $L\eta$, he would always allocate $\min r(i^p), R^p$ to process a type i^p task. The task processing problem beyond the coordination horizon is thus reduced to a single machine dynamic sequencing problem in which a subordinate has to schedule randomly arriving tasks for processing so as to maximize the expected reward. Since it is assumed that humans evaluate effects of future decisions less precisely than those of current ones, this problem is solved by treating N as infinity and scheduling future tasks by using some simple heuristics. This infinite horizon problem is formulated and solved in [15] by using a polynomial algorithm to provide approximate rewards for future job processing.

For a given resource transfer plan $[(\mu^p(\bullet), \nu^p(\bullet)]L$, DMp's task processing subproblem (7) is solved by using a dynamic programming algorithm based on the approximate rewards for future job processing obtained previously [15]. For the team resource coordination subproblem, the same dynamic programming algorithm is used to solve the aggregated individual task processing subproblems, and another dynamic programming algorithm is developed to determine the resource transfer plan over L epochs. The details of the solution algorithms are provided in [15].

Strictly speaking, the predictions generated by the task processing submodels and resource coordination submodel are not "optimal," since the omnipresent human "myopia" limitation has been incorporated and a few other simplifications have been made in the solution process. Nevertheless, since most of these limitations are related to computation—a job that computer algorithms can do much better than humans, their inclusion should not significantly affect the model's ability to predict how human teams should behave. Consequently, the model predictions at this stage are still refereed to as "normative."

E. Team Decision Making and Coordination

The task processing and resource coordination submodels are used to describe the decision making and coordination processes of both the active-leader team and the passive-leader team as follows. For an active-leader team, it is assumed that the leader knows all the subordinates' resource and (aggregated) task states, and solves the resource coordination model to determine the team's resource transfer plan. (Recall that we have assumed a centralized information structure). The leader then implements immediate resource transfer decisions. However, he may or may not announce his future resource transfer plan, $[(\mu^*(\bullet), \nu^*(\bullet)]_L$, which is needed by the subordinates to plan their future task processing. If he announces it, the team is said to be explicitly coordinated. Otherwise, a subordinate would need to solve his own version of the resource coordination submodel to anticipate the leader's future resource transfers, i.e., implicit coordination is used. With the team resource transfer plan determined, each subordinate can then employ his own task processing submodel to make his task processing decisions.

In a passive-leader team, the leader does not participate in on-line decision making, and is considered as absent in the dynamic decision-making process. Each subordinate is assumed to know the team's resource and (aggregated) task states, and uses both the resource coordination submodel and task processing submodel to make his decisions. At time k, DMp first uses his version of the resource coordination submodel to determine his own resource transfer decisions and to estimate the resource transfers from other subordinates. With the team resource transfer plan given, DMp then employs his own task processing submodel to determine his local task processing.

After the resource coordination and task processing submodels are solved by individual team members at time k, only the immediate decisions are implemented. In the case of an active-leader team, the leader may or may not announce his future resource transfer plan. At the next time $k+1$, the leader and subordinates resolve the same submodels once again based on the new task and resource states to make their next decisions. The decision-making and coordination processes thus follow the so-called "moving window" or "rolling horizon" procedure.

Without considering individual cognitive limitations and biases, the same set of submodels is used by all DM's in both the active-leader team and passive-leader team. Consequently, the normative model predictions of an active-leader team and a passive-leader team will be the same. Differences would only show up if model parameters (or structure) were to change differently across the two types of teams. It is for this reason that our experimental design considers both types of teams. As the normative–descriptive models are developed, the analytic differences between the teams will emerge, as will the differences among DM's within a team.

III. The Hierarchical Resource Allocation (HRA) Experiment

The second step of the normative–descriptive approach is to design and conduct an experiment to see how human teams actually behave. The experiment will also help validate specific team organizational and behavioral hypotheses. Before presenting the experiment design, short descriptions of the hierarchical resource allocation (HRA) experimental setup and screen displays are given.

The HRA experiment was developed on four SUN workstations connected via an ETHERNET local area network. The workstation screens for the leader and subordinates are shown in Figs. 2 and 3, respectively. The upper half of both screens displays active tasks, their resource requirements, values and deadlines, and gives the same picture to all DM's of the team. Tasks arrive randomly at the top of the screen and move downwards at a constant speed. A task's current time available is thus proportional to the distance between the task and the bottom line of the upper half screen. Once resources are allocated to a task, the task icon changes so that DM's know that processing has just started. For simplicity, all tasks are assumed to have the same processing time requirement. When the processing is finished, the icon disappears from the screens.

The resource dynamics is displayed differently for the leader and subordinates. Each subordinate can see his own resource state through a chart at the lower right corner of the screen, showing how many resources are tied-up and when they can be used again. Below the chart, he can see the resource ownership of the team (who owns what). The leader's display only shows the team's current resource ownership and current tied-up status, but not the detailed time-to-return dynamics. Note that if the leader had perfect memory, he would be able to deduce detailed resource dynamics from the task information provided to him.

Communications on resource coordination are done through formatted messages. For an active-leader team, the leader can announce his intended next resource transfer. Subordinates can only request resources from the leader. For a passive-leader team, the leader sits as an observer, and subordinates

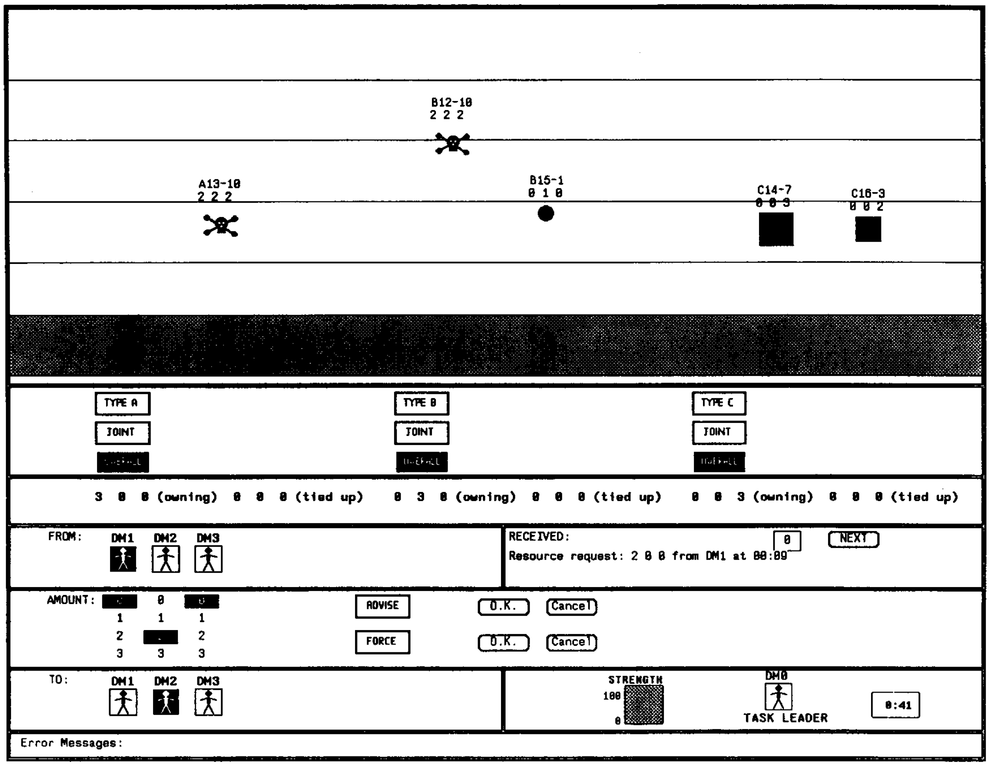

Fig. 2. Leader's workstation screen.

request/obtain resources from each other. All communication messages are transmitted without a delay, and are shown on the screens of relevant DM's.

The control option interface implements task processing and resource transfer decisions. For a passive-leader team, control options of a subordinate include selecting which task to process and the amount of (each type of) resource to allocate, and selecting the subordinate and the amount of resources to transfer. For an active-leader team, decisions on resource transfers are carried out solely by the leader. In both cases, a resource transfer is subject to a fixed time delay.

Finally, each team member has a performance display indicating the team's current strength. In each trial, the team strength starts with an initial value equal to the total task value presented in the trial. Whenever an unprocessed task passes the deadline or a task is processed with less than the required resources, its loss, computed according to (6b), is deducted from the team strength. The team strength is displayed as a percentage of the initial team strength.

A. Experimental Hypotheses

The primary assumption behind our empirical study is that different levels of leader's involvement will result in different team decision-making, coordination, and adaptation strategies under various load conditions. Specifically, it is hypothesized that:

1) an active-leader team would surpass a passive-leader team in performance (final team strength);
2) the major contribution of an active leader would be to increase the efficiency and effectiveness of coordination, i.e., better joint task processing;
3) an active leader would steer the team toward more joint actions, i.e., more joint task processing;
4) under high tempo conditions, a passive-leader team may break up into a collection of individual DM's, as opposed to a coordinated team; and
5) an active leader (resource coordinator) would reduce the workload of his subordinates.

B. Independent Variables

The focus of the HRA experiment is to measure how leader's involvement, external workload, and coordination incentives affect a team's decision-making, coordination, and strategy adaptation processes. To assess the experimental hypotheses and to establish a set of experimental results to be compared with model predictions, three independent variables were chosen: 1) leader's involvement, 2) task tempo, and 3) coordination incentive.

1) *Leader's Involvement:* The leader can be either active or passive as explained previously.
2) *Tempo:* In the experiment, tasks arrive randomly in time according to a Poisson process. Tempo is manipulated by varying the arrival rate of the Poisson process, i.e., the average number of tasks arriving per minute. Tempo has a direct impact on a team's workload. Both low and high tempo conditions were implemented.

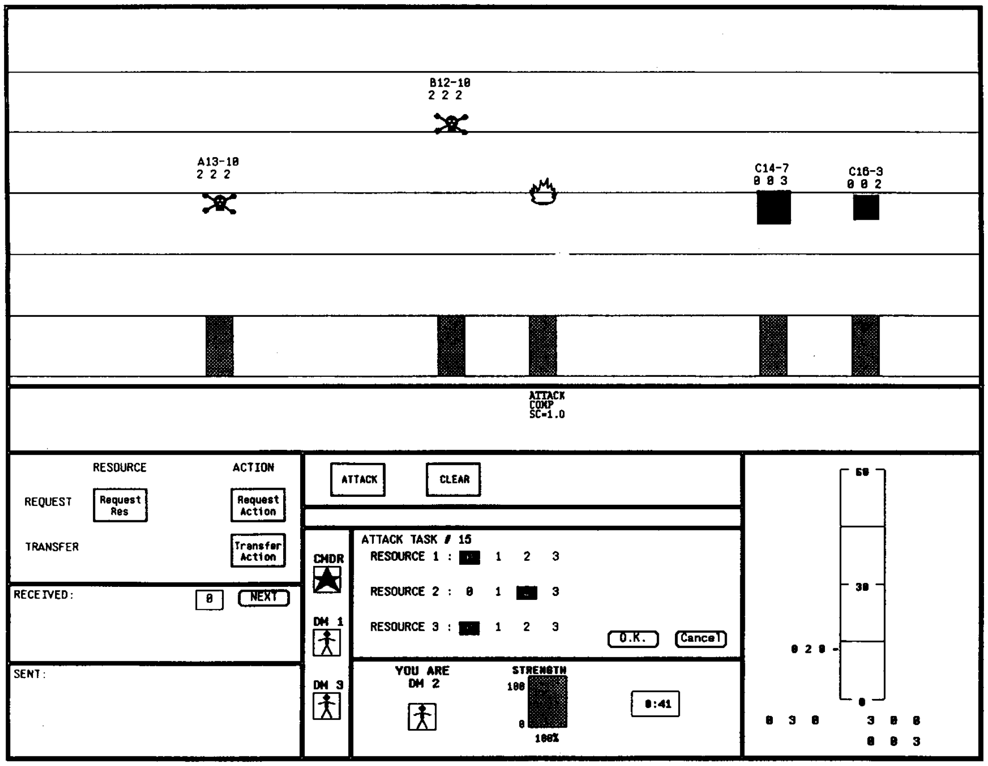

Fig. 3. Subordinate's workstation screen.

3) *Coordination Incentive:* According to the problem description, joint tasks are the only reason for resource coordination. For simplicity, all joint tasks have the same value in a trial, and the value can be interpreted as an incentive for coordination. By manipulating this value, the need (or the incentive) for resource coordination can be varied. In the experiment, the joint task value was varied over three levels: low, medium, and high.

Following our previous experimental designs [13], [20], the initial time available and processing time requirement of all tasks were chosen as 150 s and 30 s, respectively. The resource transfer delay is 15 s. Subordinate p initially owns three units of type p resource. He is faced with three types of individual tasks, requiring one, two, or three units of type p resource and having values of one, three, or seven, respectively. He is also faced with one type of joint tasks, requiring a total of six units of three types of resources subject to the constraint that he cannot allocate more than two units of his own type of resource. This formulation is consistent with the cost structure defined in (6).

The specific levels of the second and the third independent variables, and the percentage of joint tasks in the task population were determined through queueing analysis presented in [13]. Arrival rates of 3.75 tasks/minute and 6.0 tasks/minute generated model-predicted busy periods of 77% and 96%, and were chosen as the rates for low and high tempo, respectively. The percentage of joint tasks in the task population was chosen as 30%. With this choice, the probability of having one active joint task for a subordinate at a given time is 0.32 and 0.42 for low and high arrival rates, respectively. The probabilities of having two or more joint tasks at the same time are 0.024 and 0.032 for low and high arrival rates, respectively. Finally, the three levels of joint task value were chosen as 10, 15, and 20, respectively. With these values, the queueing model shows that dynamic resource transfers are needed to achieve the best team reward. That is, the team cannot ignore joint tasks in the case of low joint task value, and cannot ignore individual tasks in the case of high joint task value if the team is to optimize the total score.

C. Dependent Variables

Four groups of measures (dependent variables) were collected during the experiment. They are loosely categorized as performance, strategy, coordination, and workload measures. This classification is by no means exclusive, as it is often possible to put one measure into more than one group.

Performance: The team performance is measured by the final team strength, which is the ratio of total task value earned to that presented in the trial.

Strategy: This category of variables indicates which types of tasks are processed and how well they are processed. Four measures were recorded to reflect a team's joint task processing behaviors:

1) The percentage of reward obtained through processing joint tasks;

2) The average accuracy score of joint tasks processed, where the accuracy score of a task is calculated according to (6a); and
3) The average slack time for joint tasks processed. A task's slack time is its time available at the start of processing minus its time required.

Coordination: This category of variables measures how a team exchanges information, transfers resources, and utilizes transferred resources.

Four measures were recorded in the experiment:

1) The number of resource requests;
2) The number of resource transfers;
3) The number of times that an active leader announced his resource transfer plan;
4) Coordination resource utilization, defined as the fraction of time that transferred resources are used for joint task processing. Specifically, for a unit of transferred resource that a subordinate receives, let T_t be the total time period that the subordinate has the resource and T_j be the period of time that the resource is actually used for joint task processing. The transferred resource utilization for this unit is defined as T_j/T_t. Coordination resource utilization is the average transferred resource utilization.

Workload: The workload of each DM is obtained by using the team subjective workload assessment technique (SWAT) described in [17].

D. Experimental Procedure

Three teams, each consisting of four undergraduate and/or graduate engineering students at the University of Connecticut, were openly recruited. It turned out that members in each team were close friends. Before the formal experiment, teams were trained for about 20 hours under statistically similar scenarios without collecting data until their performance roughly asymptoted and they considered themselves as "ready." These training sessions attempted to reduce any learning effects that could taint results in the formal experiment. During the training sessions, a leader was selected by the subjects within each team, and then fixed during the formal experiment.

In the formal experiment, there were two scenarios run for each of the six load conditions (tempo $\times$ joint task value). Each team experienced these 12 scenarios twice, once as a passive-leader team and once as an active-leader team. The sequence by which each team experienced the specific scenarios was randomized so as to minimize the trial ordering effect. Each trial ran about thirteen minutes, where the exact finishing time was randomized to reduce the effect of "last second" decisions. Before each trial, the subjects were given information about the trial and were allowed to discuss their strategies. Once the trial started, the subjects were only allowed to communicate by using formatted computerized messages as previously described.

IV. Experimental Results

A two (leader's involvement) by two (tempo) by three (joint task values) analysis of variance (ANOVA) was performed for all dependent variables. The ANOVA generates p, the probability of making an error in claiming that a dependent variable is affected by different levels of an independent variable. A p value less than 0.05 is accepted as significant; $p < 0.10$ is marginally significant and is considered as a "trend." Besides the significance of an independent variable, the ANOVA method also identifies significant interactions between two or more independent variables, i.e., the cross or nonlinear coupling of independent variables that affects a particular dependent variable.

The purpose of the experiment is to assess experimental hypotheses, and to observe how active-leader teams and passive-leader teams differed in their strategies. The effects of leader's involvement are first examined, followed by the cross effects of leader's involvement and coordination incentive, and finally the cross effects of leader's involvement and tempo.

A. Effects of Leader's Involvement

Figs. 4–6 compare the two levels of leader's involvement with respect to coordination resource utilization, joint accuracy score, and workload of subordinates across the different levels of tempo and joint task value. The ANOVA indicated that the following first-order effects of the leader's involvement were significant. (Disproportionate cases corresponding to cross or nonlinear effects will be discussed later.)

1) Although not shown, active-leader teams had a significantly higher final team strength (67.1%) than that of passive-leader teams (62.9%) with $p < 0.001$. In virtually every condition the final team strength of an active-leader team was about 4.5% higher than in the passive-leader case.
2) Overall, active-leader teams had a significantly higher coordination resource utilization (49.2%) than that of passive-leader teams (44.5%) with $p < 0.001$.
3) Overall, active-leader teams exhibited better joint accuracy scores (61.0%) than that of passive leader teams (55.2%) with $p < 0.005$.
4) Subordinates in active-leader teams reported a lighter workload (26.4) than those in passive-leader teams (38.4) with $p < 0.002$.

Consequently, the hypothesis that an active-leader team would surpass a passive one in performance is verified. Moreover, since the joint accuracy score and coordination resource utilization are indicative of the effectiveness and efficiency of team coordination, our hypothesis that a leader would increase the effectiveness and efficiency of coordination is also verified. Finally, the hypothesis that an active leader would reduce the workload of his subordinates is confirmed.

The hypothesis that an active leader would steer a team toward more joint actions is reflected via dependent variables such as the percentage of reward obtained through joint task processing, and the average slack time of joint tasks processed. However, these were not significant at $p = 0.05$ with respect to leader's involvement, and so it was concluded that the data were insufficient to confirm the hypothesis.

Our main conclusion is that an active-leader team can coordinate its resources better than a passive-leader team.

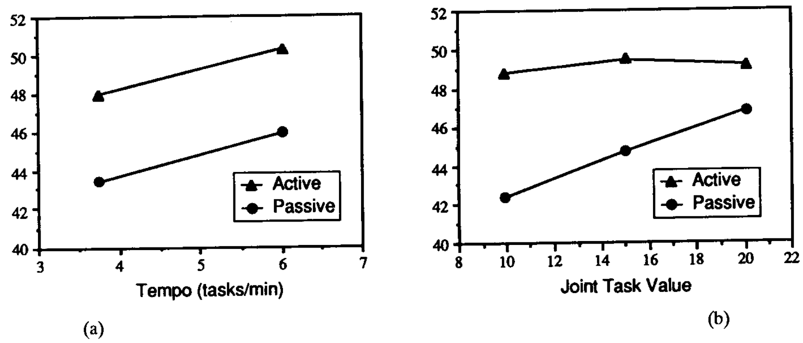

Fig. 4. Coordination resource utilization versus (a) tempo and (b) joint task value

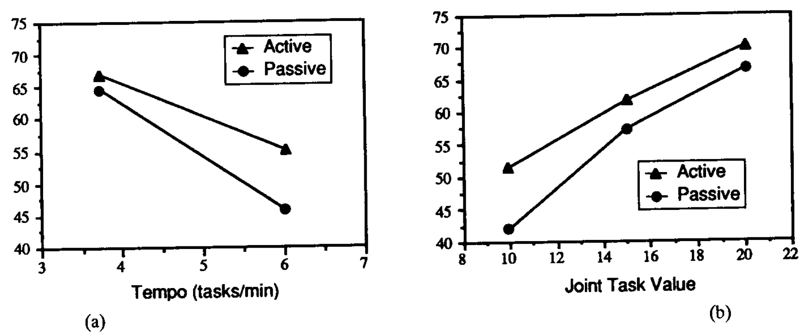

Fig. 5. Average joint task accuracy score versus (a) tempo and (b) joint task value

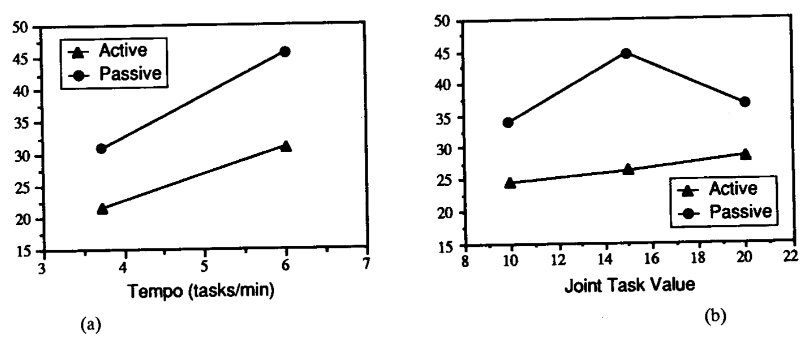

Fig. 6. Subordinates' subjective workload versus (a) tempo and (b) joint task value.

Although some other dependent measures were not statistically significant, they do consistently support this belief. For example, active-leader teams obtained a higher percentage of their reward from processing joint tasks than did passive-leader teams, and active-leader teams had longer average slack time for joint tasks than did the passive-leader teams. Moreover, it was found that the coordination resource utilization (Fig. 4) was the only measure that was significantly affected by different levels of leader's involvement, but not by different levels of tempo nor joint task value.

B. Interactions between Leader's Involvement and Coordination Incentive

The interaction between leader's involvement and joint task value is significant only for average slack time on joint tasks processed with $p < 0.05$. The result is shown in Fig. 7. It can be seen that active-leader teams have about the same 30 s joint slack times over all three levels of joint task value. The joint slack time for passive-leader teams, however, increases sharply for conditions with high joint task value.

Insensitivity of some other measures to changes in the independent variables is observed in active-leader teams. As shown in Figs. 4(b) and 6(b), active-leader teams have about the same coordination resource utilization and the same subordinate workload over three levels of joint task value. Passive-leader teams, on the other hand, seem to have a somewhat higher coordination resource utilization but a lower workload for the high joint task value condition—although these two observations are not statistically significant. When the results on joint task slack time of Fig. 7 is factored in, we are led to believe

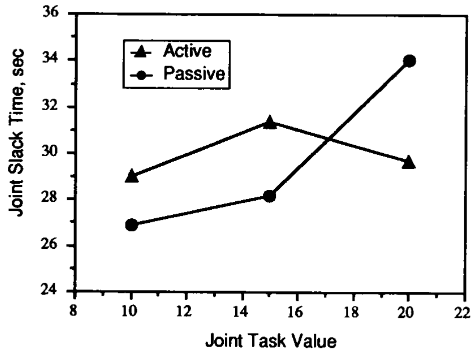

Fig. 7. Average joint task slack time versus joint task value.

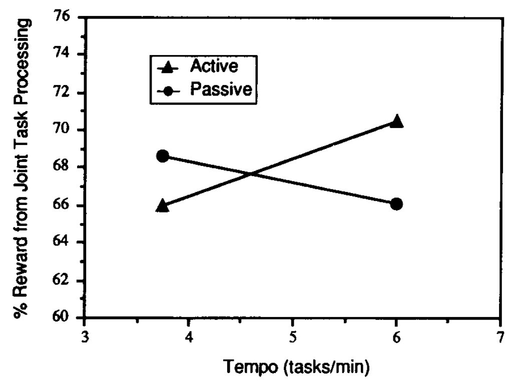

Fig. 8. %Reward obtained from processing joint tasks versus tempo.

that an active-leader team utilizes the same strategies over different levels of coordination incentive, whereas a passive-leader team adopts a different strategy for conditions with high joint task value. The actual strategy adaptation process, however, is difficult to address based purely on empirical data, but will be discussed in the normative–descriptive modeling section that follows.

C. Interactions between Leader's Involvement and Tempo

No dependent variables were significant with $p < 0.05$ for the interaction between leader's involvement and tempo. Two dependent variables have p values less than 0.09: the average joint accuracy score and the % reward obtained through processing joint tasks, as shown in Fig. 5(a) ($p < 0.07$) and Fig. 8 ($p < 0.09$), respectively. It can be seen that at low tempo, passive-leader teams achieved about the same joint task accuracy score as did active-leader teams, but obtained more of its total reward from processing joint tasks than did active-leader teams. At high tempo, however, passive-leader teams had a lower average accuracy score, and (compared to active-leader teams) less of its reward came from processing joint tasks. The results suggest that at high tempo, a passive-leader team is not able to or may be unwilling to maintain its coordination actions at the same level as that of an active-leader team. A similar phenomenon was also observed in a previous study [20] involving three-person parallel teams. As tempo increased, team members became less willing/able to coordinate their resources.

D. Epilog

Through analyzing the experimental results, most of the hypotheses that were put forward have been validated. However, an empirical study alone cannot tell how strategy adaptation happens, nor why it happens. To overcome these shortcomings and to provide insight to the human team decision-making and coordination processes, the normative–descriptive approach that brings together how human teams should act and how they actually act will be presented next.

Before starting the modeling effort, it is worthwhile noting that two of the coordination measures, the number of resource requests and the number of times that an active leader announced his intended next transfer, were not statistically significant with respect to independent variables. In fact, two out of three teams rarely transmitted any messages in the experiment. Few communication messages indicates that the teams coordinated implicitly for the most part, i.e., team members anticipated the (need for) resource transfers without relying on explicit communication messages. This was made possible in the experiment by providing nearly centralized information to all DM's of a team.

V. Normative-Descriptive Models

In this section, normative model predictions are compared with experimental results. Human cognitive limitations and biases (descriptive factors) are identified and incorporated into the normative models to bring model predictions in-line with experimental results.

A. Model-Data Comparison

As stated in Section II, the normative models for both active-leader and passive-leader teams use the same resource coordination and task processing submodels. Therefore, under the normative construct, active-leader teams and passive-leader teams would perform identically. Different strategies in active-leader teams and passive-leader teams observed in the experiment must be explained by introducing descriptive factors (i.e., human limitations and biases) into the normative models.

Fig. 9 compares normative model predictions with experimental results for coordination resource utilization, average joint accuracy score, % reward from joint tasks processed, and average joint slack time, across the three levels of joint task value. The model results are obtained using a simulation shell where the normative algorithms are imbedded. For each independent variable condition the simulation is exercised using the same task arrival scenarios as those given to human teams. The resulting model outputs are then averaged for comparison with the data. A time unit of one second is used in the model, corresponding to the time update interval in the real-time experimental software. Five seconds are added to the task processing time to account for human operational

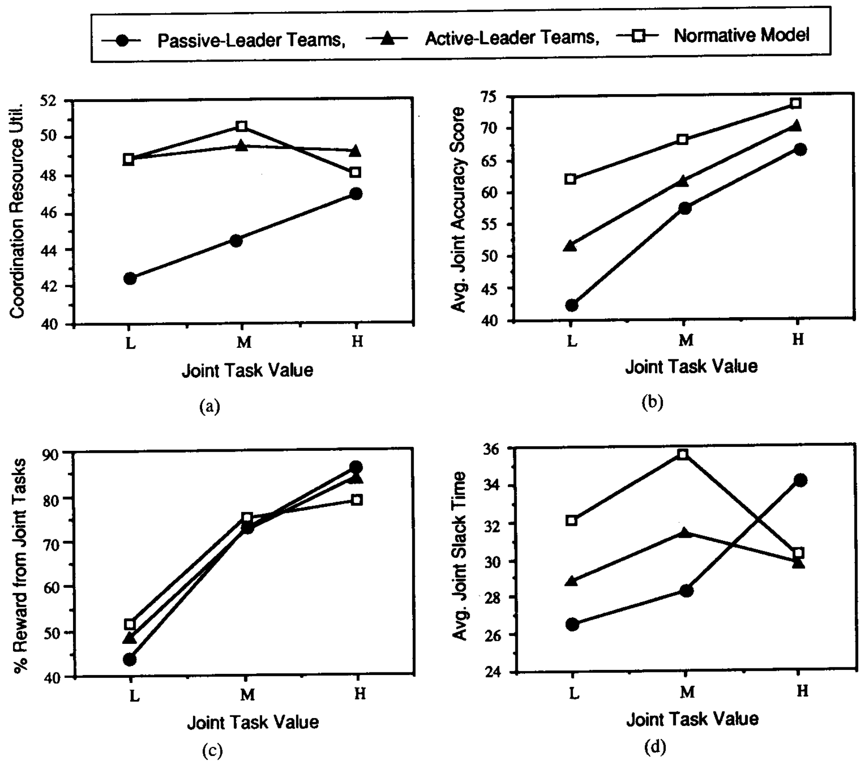

Fig. 9. Normative model predictions versus human team results (joint task value).

delay. In the resource coordination model, the time scale is aggregated by a factor $\eta = 35$. The planning horizon is chosen as two epochs, a choice consistent with our previous findings on human planning horizon [13], [20].

In Fig. 9, similar patterns/trends are seen between model predictions and the data from active-leader teams across three levels of joint task value. The trends are not quite so similar between model predictions and the passive team data. Note that model predictions are based on the same set of parameters over all conditions, so that any strategy changes within the model are caused by the need to "optimize" performance. The similar patterns between active-leader teams and model predictions, especially with respect to coordination resource utilization, gives support to our previous claim that an active-leader team's decision-making behavior is not (in and of itself) directly affected by changes in coordination incentive. The different patterns between model predictions and passive-leader teams suggest that the opposite is true for passive-leader teams. That is, a passive-leader team adapts its strategy in a direct way to coordination incentive.

In Fig. 10, similar model-data comparisons are made across two levels of tempo. The active-leader team data and model predictions show similar patterns. Passive-leader teams, on the other hand, had lower coordination resource utilization, processed joint tasks less accurately, obtained smaller percentage of reward through joint tasks at high tempo, and started processing joint tasks later as compared to model predictions. A passive-leader team thus cannot coordinate its joint actions to the extent that it "should" have as prescribed by the normative model.

The comparisons in Figs. 9(a)–(d) and 10(a)–(d) indicate that an active leader can raise a team's joint actions to a level consistent with normative predictions, i.e., how a team "should" perform. The lack of an active leader, on the other hand, leads to a lower level of joint actions. Clearly, the presence of a leader strongly affects a team's coordination behavior. On the basis of these results and our interpretations, coupled with the different response patterns between active-leader teams and passive-leader teams, we have concluded that a separate normative–descriptive model should be developed for each of the two team conditions.

B. The Normative–Descriptive Models for a Passive-Leader Team

From Figs. 9(a)–(d) and 10(a)–(d), it can be seen that passive-leader teams have a lower level of actions on joint tasks than what the model predicts. A "self-centered" (or "egocentric") bias [18], wherein an individual over-values his own responsibilities (tasks), is put forward as a major reason for these differences. A subordinate, by overvaluing his own tasks, would be unlikely to transfer his resources to another DM and would be more likely to hold on to another DM's resources for a longer time. This would lead to a smaller percentage of reward obtained from joint tasks, a lower average joint accuracy score, a lower coordination resource utilization, and

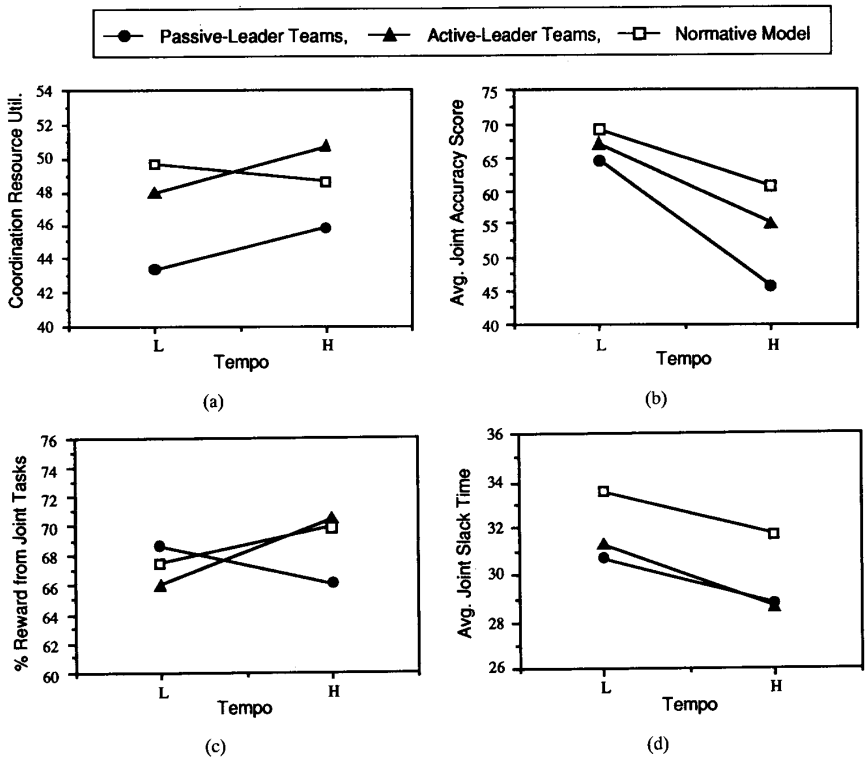

Fig. 10. Normative model predictions versus human team results (tempo).

a smaller joint slack time than model predictions. The self-centered bias is incorporated into our model by increasing the values of each subordinate's own tasks in both his resource coordination and task processing submodels. An increase of 15% was found to best match model and data results. Note that with this modification, no two DMs' submodels are the same |•| the overall "team" model has given way to separate and (parametrically) different "individual" submodels.

After this modification, model predictions were found to match human data quite well—except for the high tempo and high joint task value condition. Here, human teams had a better coordination resource utilization, a higher percentage of reward obtained by processing joint tasks, a larger average joint slack time, but a lower joint accuracy score than model predictions. Also, the passive-leader teams had a larger joint slack time than in other conditions, but with the same level of workload as in other high tempo conditions. These results are contrary to what one might expect. Since the high tempo-high joint task value case represents the most difficult resource coordination and job scheduling condition, a high workload and a short joint task slack time would be expected. The empirical findings and model-data comparisons suggest that an adaptation in team strategy is taking place to reduce decision alternatives in order to concentrate on joint task processing. This phenomena has been observed in our previous work [14], [20], and was explained as a "filtration strategy" (eliminating actions on some tasks or elimination by aspect (EBA), see [23]. A filtration strategy was implemented in the models by neglecting all active individual tasks in the resource coördination submodels for those conditions with high tempo and high joint task value. This results in quicker transfers of resources to process joint tasks. Fig. 11(a)–(f) shows that the final normative–descriptive model results match human data well. Over all 36 measures (six dependent variables over six conditions), 32 fall within one standard error, and four fall within two standard errors (SE) of the data.

C. The Normative–Descriptive Model for a Active-Leader Team

Now go back to Fig. 10 to compare normative model predictions versus data from active-leader teams. It can be seen from Figs. 10(b)–(c) that under high tempo, both the human teams and the model obtain about the same percentage of reward through processing joint tasks. The human teams, however, processed joint tasks with less accuracy. Unfortunately, as we begin to search for descriptive factors to explain these results, we quickly learn that it is difficult to separately identify the descriptive factors for the leader and those for the subordinates because of the coupling of their decision-making behaviors. However, it is reasonable to believe that the self-centered bias identified for subordinates in passive-leader teams will still exist under the presence of an active leader. Thus, the first step in building a normative–descriptive model for the active leader team is to incorporate the self-centered bias into the subordinates' task and resource submodels as was

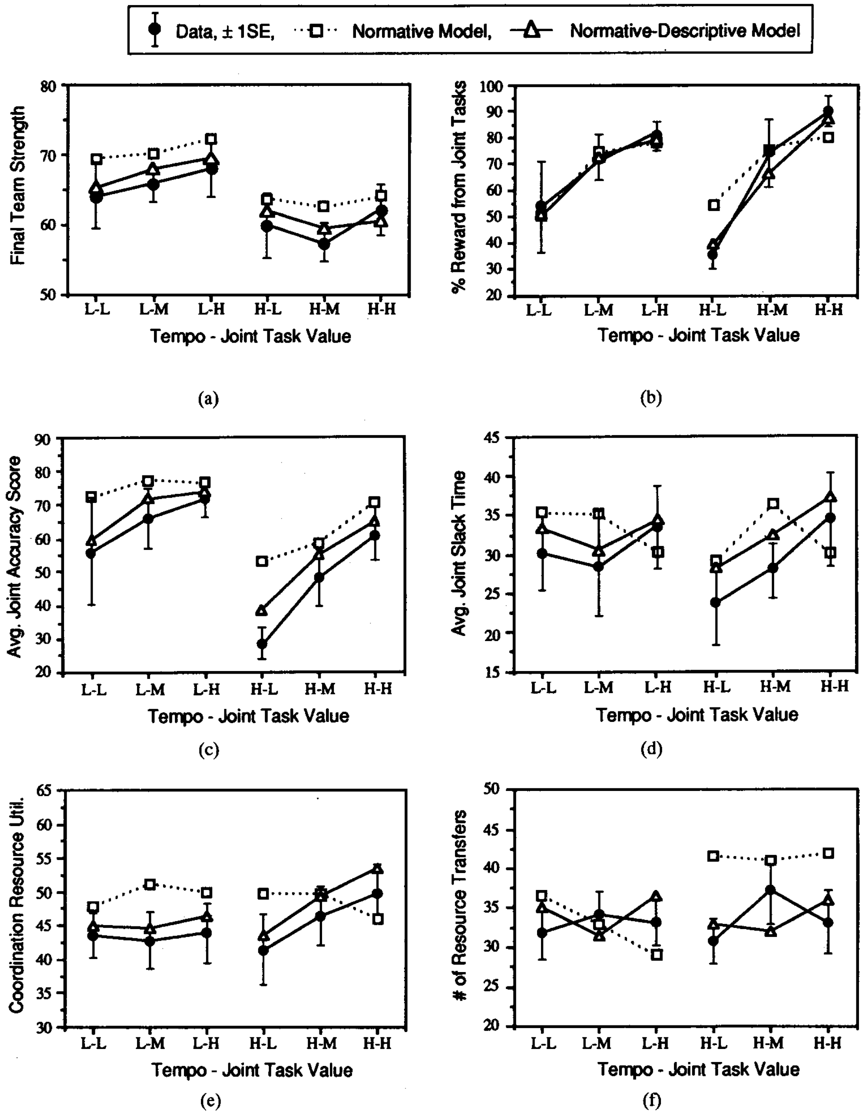

Fig. 11. Normative–descriptive model versus human data (passive-leader teams) descriptive factors: Self-centered bias; filtration strategy at H-H condition.

done in the passive-leader case. Fig. 12 compares this first stage model with human data with respect to the percentage of reward obtained through processing joint tasks over both tempo and joint task value. It can be seen that significant differences occur for conditions with high tempo, where the human teams achieved a larger percentage of reward from joint task processing. Note that joint task processing in an active-leader team is essentially determined by the leader's resource transfers. Since the leader's major role is to assist in the processing of joint tasks, he would be prone to treating joint tasks as "his baby," In this way, we consider that the leader is also affected by the self-centered bias, in which he over-values joint tasks. This descriptive factor was implemented by increasing the values of all joint tasks by 15% in the leader's resource coordination submodel.

Incorporating this single descriptive factor for the leader, the normative–descriptive model for the active leader case successfully mimics human decision-making behaviors as shown in Fig. 13(a)–(f). Over all 36 measures, 34 fall within one standard error, and two fall within two standard errors of the data.

D. Summary

Comparisons between normative model predictions and human data supports our previous empirical claims that an active-leader team is less sensitive to variations in tempo and coordination incentive, whereas a passive-leader team explicitly changes its strategy as a function of coordination incentives (especially under high incentive and high tempo conditions). The passive leader team has difficulty coordi-

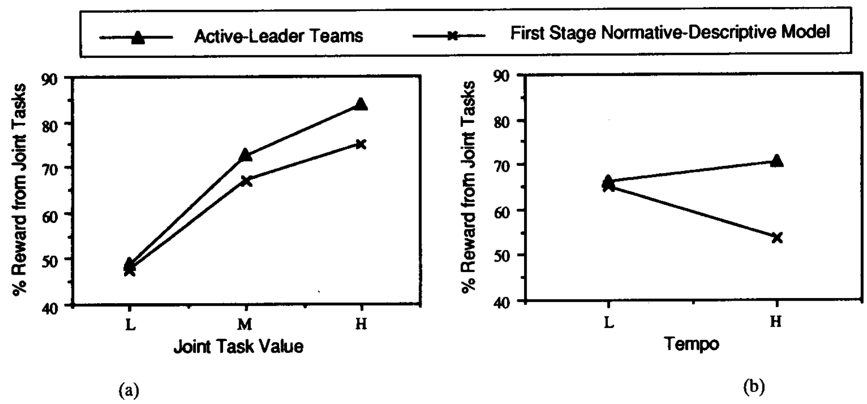

Fig. 12. First stage normative–descriptive model for active-leader teams descriptive factor: Self-centered bias for subordinates.

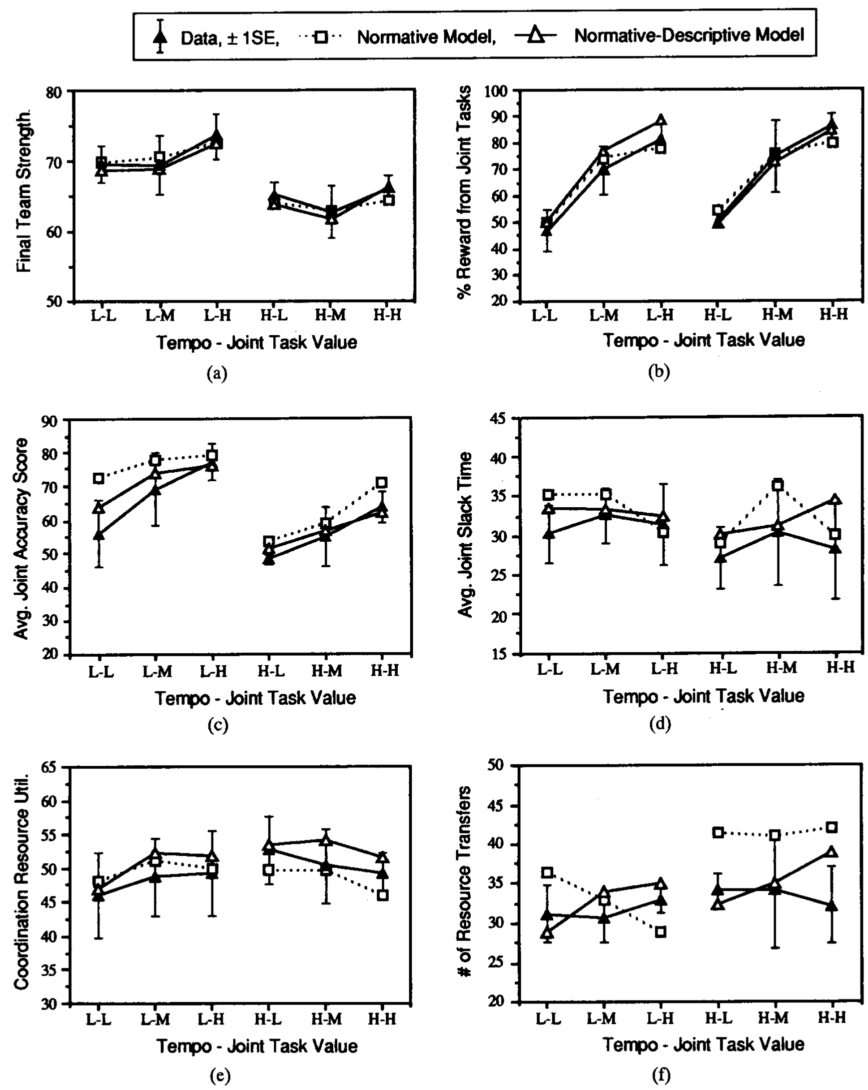

Fig. 13. Normative–descriptive model versus human data (active-leader teams) descriptive factors: Self-centered bias for leader and subordinates.

nating its actions for high tempo conditions. Moreover, it is identified that the subordinates' "self-centered" bias is the major contributor to the low level of joint task actions seen for passive-leader teams. The leader in an active-leader team is also prone to this self-centered bias through his overvaluing of joint tasks. By incorporating these descriptive factors into the normative models, the predictions of normative–descriptive models match human data well for most measures collected.

VI. Conclusion

The normative–descriptive modeling approach is a framework that brings together how human actually act and how we believe they ought to act. By being able to identify human team biases that can have negative effects on overall system performance, and to provide models that can yield realistic predications of actual human behavior, the approach provides a tool that ultimately can be used to suggest design modifications to enhance organization performance. Using the normative–descriptive approach to study a distributed hierarchical team resource allocation and task processing problem, this paper has made the following three contributions.

First, we have considered hierarchical teams, which are more important (but more difficult) to study than parallel teams. More importantly, we moved away from the "centralized" modeling approach that was used in most of the previous studies, and developed distributed models to predict individual DM's decision-making and team coordination processes. This distributed modeling approach more closely resembles the actual decision-making processes in a distributed environment, and is essential for studying team coordination.

Second, driven by the models, a multihuman experiment was designed and operationalized. The experimental results indicated that:

1) an active-leader team is more effective and efficient than a passive-leader team in resource allocation and task processing, and yields a lighter subordinate DM workload;
2) a passive-leader team may break into a collection of individuals under high workload conditions, where an active-leader team can still coordinate its actions; and
3) a passive-leader team explicitly changes its coordination strategy in response to variations in coordination incentives, whereas an active-leader team is not sensitive to such variations.

Finally, by comparing human data with normative modeling predictions, it was found that an active-leader can raise a team's joint actions to the level prescribed by a normative model, whereas the lack of an active leader induces a lower level of joint actions. The comparisons also helped identify human biases which are essential for the understanding of human team decision-making and coordination processes. The biases identified were: the "self-centered" bias wherein people overvalue their own tasks, and elimination-by-aspects wherein humans reduce decision alternatives. These biases have been identified in several previous studies on parallel team resource allocation problems. Their appearance over different efforts signifies their important role in team decision-making behaviors. Incorporating these human biases into the normative models, our final contribution of having developing a successful normative–descriptive model was achieved.

The current study and model-data results can offer suggestions for improving team performance. Specifically, to overcome the self-centered bias, team members should be trained more positively in evaluating each other's responsibilities. To attain better coordination under high tempo conditions, an active-leader structure would be recommended. Finally, since an active-leader team is less sensitive to variations in the external conditions than a passive-leader team, we tend to believe that the active-leader team is more suitable for dynamic and stressful environments.

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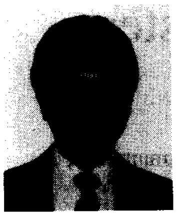

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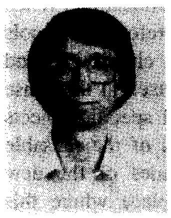

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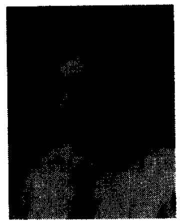

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Dr. Kleinman was the Program Chairman for the 1989 IEEE International Conference on Systems, Man, and Cybernetics. He is also a Technical Committee Chair (Human Decision Making) for the IEEE-SMC Society. In 1980, he was the Program Chairman for the 19th IEEE Conference on Decision and Control.