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Congruence of Human Organizations and Missions: Theory versus Data

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Congruence of Human Organizations and Missions: Theory versus Data^{*}

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ABSTRACT

In this paper, we present a methodology for quantifying the degree of fit between a mission and an organization based on the closeness between the task structure (i.e., resource requirements and task interdependence) and the DM-asset allocation across the organization (i.e., amount and distribution of resource capabilities among DMs, and organizational processes). This closeness is based on three main characteristics of organizational performance: *workload balance*, *communication requirements*, and *DM-DM dependence*. These characteristics are affected, in turn, by the *interactions* and *interdependencies* of the organizational processes and the demands of the mission scenario. Invariably, coordination is essential to achieve good performance because the information required for decisionmaking is often distributed. However, excessive DM-DM communication and coordination are harmful to performance, since they increase the processing workload/overhead that delays task execution. Performance improvements can be obtained by changing the *structure* and *processes* of an organization to decrease the requisite coordination, while balancing the levels of workload across the organization and reducing inter DM dependence.

1. Introduction^{*}

An organization is said to be *congruent* with its mission if its *structure* and *processes* are *matched* to the environmental parameters [1], [10]. The degree of “match” (“fit”) between an organization and a mission can be quantified based on its *performance* or *structure*. The concept of performance-based congruence is relative: the degree to which an organization is congruent to a mission is obtained by comparing its performance to that of an “optimal” organization for the same mission. However, finding this optimal organization is computationally prohibitive for real-time mission monitoring, re-planning and decision support. On the other hand, human-in-the-loop simulations, needed for performance evaluation, present a challenge

in uncertain and dynamic environments, where the effort to achieve *dynamic congruence* forces organizations to adapt, while they continue to operate [11]. In situations involving dynamic and uncertain environments, we turn to the concept of structure-based congruence measures.

In this paper, we argue and provide evidence that structure-based congruence is a multi-dimensional concept involving resources, task structure and organizational processes (e.g., workload balance). We define *structure-based* congruence measures by evaluating the closeness of task parameters with the organizational structure and processes. Based on substantial evidence in the management literature [1], [10], [5], and our normative organizational design process [8,9] developed as part of the Adaptive Architectures for Command and Control (A2C2) program, we hypothesize that the better an organization is matched to its mission, the better will that organization perform. In order to validate the normative

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predictions, namely that structure-based congruence leads to performance-based congruence, we designed and conducted a team-in-the-loop A2C2 experiment using two different organizational structures and two different missions. The first organizational structure was to be congruent (matched) with the first mission, but highly mismatched (i.e., exhibit low congruence) to the second mission. The reverse is true for the second organizational structure. The experiment – number 8 on the list of A2C2 empirical milestones – was conducted at NPS in August and November 2002. The objective of this experiment was to compare theoretically predicted and experimentally observed measures of congruence between the missions and the organizations. In this paper, we describe how we reverse synthesized missions to generate mismatches with organizations, and how we *modeled* the specific structural mismatches and matches among the corresponding elements of organizations and missions. The model serves as the basis of our structure-based congruence framework.

In our work, the congruence between an organization and a mission is measured by the structural interaction between the organization and its environment. Informally, the incongruence between the organization and a mission can be perceived as the structural fit depicted in Fig. 1.1.

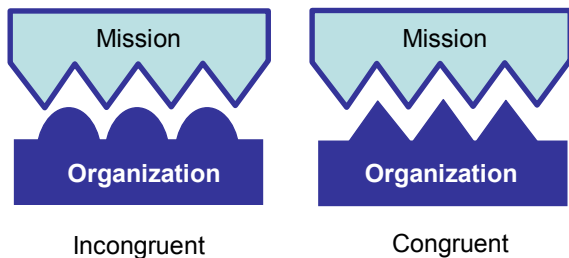


Figure 1.1. Informal visualization of (mis)match between a mission and an organization

A *congruent* organization minimizes the levels of workload imbalance, communication requirements, and DM-DM dependence. Our methodology is based on identifying these three characteristics via a fit of specific structural parameters of organizations and missions. The parameters include:

- Organization: DM-asset allocation and organizational structure (authority and communication).
- Mission: task density, locations, information flow, task precedence, and resource requirements.

The rest of the paper is organized as follows. Section 2 describes how we represent missions and organizations. Section 3 formalizes organizational processes and measures for evaluating the degree of congruence. Section 4 discusses the task execution model to evaluate the delays associated with task processing and communication. Section 5 distinguishes among the three dimensions of congruence: resource, task network, and workload balance congruence. Sections 6 & 7 describe the application of our congruence hypotheses in the design of Experiment 8. Section 8 concludes with the summary and future extensions.

2. Representing Missions and Organizations

2.1. Tasks and Task Graphs

A fundamental question underlying a distributed organizational design - ‘*who should do which part of the mission?*’ - implies that the mission must be *decomposable* into a set of *entities*. These entities are generally referred to as tasks. A *Task* is an activity that entails the use of relevant resources (provided by organization’s assets) and is carried out by an individual DM or a group of DMs to accomplish the mission objectives. Every task in itself represents a “small mission”, and can oftentimes be further decomposed into more elementary tasks.

In our model, we characterize a task T_i ($i = 1, \dots, N$, where N is the number of tasks) by specifying the following basic attributes:

- Task release time b_i (time at which the task appears in the mission scenario);
- Task processing time window, \hat{t}_{ai} (maximal time available from the start of task execution to its finish; this time window is used to synchronize assets assigned to this task: it indicates the time window during which these assets must be “applied” to execute the task);
- Task processing time t_i (the interval between the time the first asset starts executing the task and the time at which the last asset finishes the task; the task processing time must not exceed the task processing time window: $t_i \leq \hat{t}_{ai}$);
- Task accuracy α_i ;
- Task start time s_i (corresponding to the time that a task execution is started, and obtained during mission execution);

- Geographical location of task (x_i, y_i) in a state space. The location parameters can be used to compute the “distance” d_{ij} between tasks T_i and T_j ;
- Resource requirement vector $[R_{i1}, R_{i2}, \dots, R_{iL}]$, where R_{il} is the number of units of resource l required for successful processing of task T_i ($l = 1, \dots, L$, where L is the number of resource types);
- Task value ω_i (task value reflects the importance of individual tasks – either on a relative or absolute basis – and is taken as an indicator of the commander’s intent or priority; all tasks are not equally important).

A *Task Graph* is a dependency diagram that details the following interrelationships among tasks:

- task precedence;
- inter-task information flow; and
- input-output relationships between tasks.

A directed acyclic task-precedence graph represents the plan to execute a mission.

2.2. Assets

An *Asset* is a physical entity of an organization that provides resource capabilities and is used to process tasks. For each asset P_m ($m = 1, \dots, K$, where K is the number of assets), we define its maximal velocity v_m and its resource capability vector $[r_{m1}, r_{m2}, \dots, r_{mL}]$, where r_{ml} specifies the number of units of resource type l available on asset P_m . Assets must be routed among task locations to execute the assigned tasks. Assets can begin to process the same task at different times, but must be synchronized to complete a task in a specified task processing window. For each asset-task pair, the asset-task engagement time $e_{m,i}$ is specified.

2.3. Decision-makers and Organizations

A *Decision-maker* (DM) is an entity with information-processing, decision-making, and operational capabilities that can control the necessary resources to execute mission tasks, provided that such an execution will not violate the concomitant capability thresholds.

An *Organization* is a *team* of human decision-makers, who coordinate their information, resources, and activities in order to achieve their common goal in a complex, dynamic, and uncertain mission environment.

As a consequence of decentralization in large-scale systems, each DM only has access to a portion of organization’s resources and, possibly, to the information available to the team. The distribution of resources among DMs and their assignment for task processing are among the key elements defining an organizational design. Team members must dynamically coordinate their resources to process their individual tasks, while assuring that team performance goals are met. The critical issues in team *resource allocation* are: *who* should own which resource, *who* should use which resource to *do what*, and *when*? An organization is therefore characterized by DM-asset allocation that provides DMs with resources to execute tasks. The allocation is formally defined by:

$$a_{mj} = \begin{cases} 1, & \text{if asset } P_j \text{ is allocated to } DM_m \\ 0, & \text{otherwise} \end{cases}, \quad (2.1)$$

for $j = 1, \dots, K$, $m = 1, \dots, D$, where D is the number of DMs in the organization. We assume that each asset is assigned to a single decision-maker, and cannot be shared during the mission: $\sum_{m=1}^D a_{mj} = 1$.

3. Organizational Processes and Measures

3.1. Mission Execution

The critical issues in team *task processing* are: *what* should be done, *who* should do what, and *when*? The processing of a mission by an organization is identified by specifying asset-to-task assignment, and the corresponding DM-task allocation:

$$y_{ij} = \begin{cases} 1, & \text{if asset } P_j \text{ is assigned to task } T_i \\ 0, & \text{otherwise} \end{cases} \quad (3.1)$$

$$u_{mi} = \begin{cases} 1, & \text{if } DM_m \text{ is assigned to task } T_i \\ 0, & \text{otherwise} \end{cases} \\ = \begin{cases} 1, & \text{if } \exists \text{ asset } P_j \text{ such that } a_{mj} = 1, y_{ij} = 1 \\ 0, & \text{otherwise} \end{cases} \quad (3.2)$$

The asset-task assignment specifies the necessary interaction among assets when processing a task. This interaction necessitates coordination among DMs that have ownership of these assets; the DMs serve as information/decision/action carriers. Specifically, to model coordination-related overhead in an organization, we define two types of coordination: *internal* and *external*. Internal coordination accounts for the need to coordinate among assets assigned to the same DM. External coordination is the inter-DM dependence that

results from cooperative processing of a task by multiple DMs.

3.2. Internal Coordination

The workload associated with operating an asset must be determined from the specifics of asset's operation and its involvement in task processing. We define an asset P_j 's *operational workload* as the aggregated load of tasks executed by this asset:

$$w(j) = \sum_{i=1}^N y_{ij} w_{ij}, \quad (3.3)$$

where w_{ij} is the workload associated with executing task T_i using asset P_j . Here, we assume that w_{ij} parameters are known, and, without loss of generality, $w_{ij} = 1$.

The *internal coordination workload* of a DM_m is defined as the aggregated workload of operating assets assigned to this DM:

$$I(m) = \sum_{j=1}^K a_{mj} w(j). \quad (3.4)$$

3.3. External Coordination

A *direct DM-DM coordination* between two decision-makers DM_m and DM_n is the aggregated time associated with simultaneous processing of the same set of tasks:

$$D(m, n) = \sum_{i=1}^N u_{mi} u_{ni} t_i = \sum_{i=1}^N \min(u_{mi}, u_{ni}) \cdot t_i. \quad (3.5)$$

The *external coordination workload* of a DM_m is the sum of its direct coordination with other DMs:

$$E(m) = \sum_{n=1, n \neq m}^D D(m, n). \quad (3.6)$$

3.4. DM Workload and Team Load Balance

Workload of a DM_m is defined as a weighted sum of the internal and external coordination workload of this DM:

$$CW(m) = W^I \cdot I(m) + W^E \cdot E(m). \quad (3.7)$$

The weights for internal (W^I) and external (W^E) coordination specify their impact on the aggregated DM workload. While the total aggregated workloads of organizations with the same mission completion time

may be similar, their performance is distinguished by the distribution of this workload among team members. We define the main performance measure of an organization as the root-mean-square of workloads of DMs in this organization:

$$\Theta = \sqrt{\frac{1}{D} \sum_{m=1}^D CW^2(m)}. \quad (3.8)$$

This measure accounts for both the mean and the variance of workloads, and, consequently, provides a measure of balance of the aggregated workloads of DMs. Given that two organizations O_1 and O_2 have the same mission completion time or task gain on a mission M , we say that organization O_1 is more congruent with this mission than O_2 , if $\Theta(O_1, M) < \Theta(O_2, M)$. That is, the better an organization is matched to its mission, the better will be its workload balance among the DMs.

3.5. Task Accuracy

When all resources required by task T_i are met, that is

$$\sum_{m=1}^K y_{im} \cdot r_{ml} \geq R_{il}, \quad (3.9)$$

then the accuracy of task completion is equal to 100%. However, in realistic applications where the resources are scarce, an organization may wish to reduce the task execution accuracy in order to achieve better timeliness. In order to accommodate timeliness-accuracy trade-off, a model of accuracy has been defined within the DDD-III simulator for scoring the DMs [6] as the average of squared ratios of the resource used to the resource required over all resource types:

$$\alpha_i = \left(\frac{1}{\hat{L}} \sum_{l=1}^{\hat{L}} \frac{\hat{R}_{il}}{R_{il}} \right)^2, \quad (3.10)$$

where \hat{L} is the number of non-zero resource requirement types of task T_i : $\hat{L} = |\{l : R_{il} \neq 0\}|$, and \hat{R}_{il} is the resources of type l used to process task T_i :

$$\hat{R}_{il} = \min\{R_{il}, \sum_{m=1}^K y_{im} \cdot r_{ml}\}. \quad (3.11)$$

The ratio of the resource used to the resource required identifies the percentage of satisfied resource for the corresponding resource type. The squaring of this ratio penalizes significant resource allocation mismatches.

3.6. Task Latency

The latency of a task T_i is defined as the time from the appearance of a task to the time when its execution starts:

$$\tau_i = s_i - b_i \quad (3.12)$$

The average task latency is given by:

$$\tau = \frac{1}{N} \sum_{i=1}^N \tau_i \cdot \delta[i], \quad (3.13)$$

where $\delta[i]=1$ if the task has been executed by the organization, and $= 0$ otherwise. The speed of command that can be achieved by the organization is inversely related to its task processing latencies. That is, the better an organization is matched to its mission, the smaller will be its task latencies and higher will be its speed of command.

3.7. Task Gain

In the presence of time-critical tasks, an organization may trade-off task accuracy versus timeliness. For an organization that is incongruent with its mission, such engagement practices may result in the same levels of task timeliness as for a congruent organization. However, this timeliness is achieved at the cost of lower accuracy. Therefore, a measure that reflects the task accuracy and timeliness tradeoff can be combined into a single measure, called the *task gain*. The task gain of a task T_i is defined as the accuracy multiplied by its value:

$$g_i = \alpha_i \cdot \omega_i. \quad (3.14)$$

In order to visualize the dynamic pattern of total gain achieved by an organization over time, we define the *accrued task gain* $G(t)$ [7] as an aggregate of task gains achieved by time t . We increment the gain function when each task T_i completes its execution (at time $s_i + t_i$) with a task gain of g_i . Therefore, the accrued task gain is computed as follows:

$$G(t) = \sum_{i=1}^N g_i \cdot \delta[i] \cdot U(t - s_i - t_i), \quad (3.15)$$

where $U(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{otherwise} \end{cases}$. Thus, $G(t)$ is a piecewise constant (i.e., stair-case) function as shown in Fig. 3.1. An organization O_1 that achieves better task latency and higher task accuracy than, say organization O_2 , on mission M is seen as having the accrued gain function

$G(O_1, M; t)$ rising at a faster rate than $G(O_2, M; t)$. On the other hand, the final values of gain functions for both organizations might be the same, since the total achievable mission gain is the same for any organization

and equal to $G^{\max} = \sum_{i=1}^N \omega_i$ (and it will be achieved in

case the organization completes all tasks with 100% accuracy). Hence, the ultimate measure of performance of an organization on a mission is the normalized area under the accrued gain function curve for this organization (see Fig. 3.1):

$$A(s) = \frac{1}{s} \int_0^s G(t) dt, \quad s \geq 0. \quad (3.16)$$

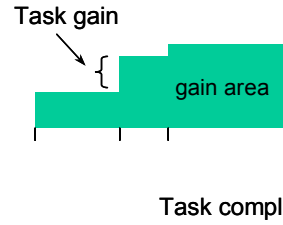


Figure 3.1. Accrued Gain Metric

We say that organization O_1 with normalized gain area $A(O_1, M; T_f)$ on mission M (where T_f is the mission end time – assumed the same for all organizations on the tested mission) is more congruent to this mission than organization O_2 with normalized gain area $A(O_2, M; T_f)$, if $A(O_1, M; T_f) > A(O_2, M; T_f)$. The computation of accrued gain and gain area is straightforward. If $\{i_1, i_2, \dots, i_n\}$ ($n \leq N$) is the sequence of task completions, then $f_{i_k} \leq f_{i_{k+1}}$, $k = 1, \dots, n-1$, where $f_i = s_i + t_i$ is the time of completion of task T_i . Hence, the accrued gain at time $t \in [f_{i_k}, f_{i_{k+1}})$ is equal to $G(t) = G[k]$, where $G[k] = G[k-1] + g_{i_k}$, $k = 1, \dots, n$, and $G[0] = 0$. Therefore, the gain area is computed as follows:

$$\begin{aligned} A(T_f) &= \frac{1}{T_f} \sum_{k=1}^n G[k] \cdot (f_{i_{k+1}} - f_{i_k}) \\ &= \frac{1}{T_f} \sum_{k=1}^n g_{i_k} \cdot (T_f - f_{i_k}) \end{aligned}, \quad (3.17)$$

where $f_{i_{n+1}} = T_f$.

4. Delay Models

4.1. Task Execution

In our simulations, we considered a simplified task execution model (Fig. 4.1). Generally speaking, we decompose the problem of task execution into several subtasks:

- 1) *identification* (task must be identified with sensor resources available to the organization);
- 2) *asset allocation* (assets must be selected to execute the task);
- 3) *task prosecution* (assets must be synchronized and routed to task location); and
- 4) *attack* (actual engagement/processing of a task by assets).

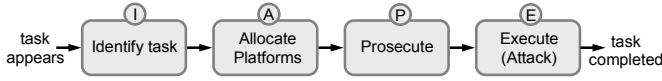


Figure 4.1. Task execution chain

In this model, identification subtask (I) and allocation subtask (A) are executed sequentially, while prosecute subtask (P) and execute subtask (E) are done in parallel (in DDD experiments, the latter subtasks involve parallel communication among DMs owning the assets in order to synchronize the assets' time-over-target to complete the task in a specified processing time window). During the identification subtask (subtask I), the DM responsible for task completion is specified. Efficient asset-to-task allocation (subtask A) is essential to effective mission execution, since it reduces the delay associated with prosecution of the corresponding task (subtask P). If a single DM, responsible for executing the task, possesses the assets with the requisite resources to complete this task with a high accuracy, the problem of selecting the most efficient asset package to execute a task can be formulated and solved (note that the actual problem of resource-task allocation is NP-hard; see [8,9]). However, the problem becomes significantly more complex when a single DM does not possess the required resources. In this case, the allocation subtask should be further decomposed into elementary subtasks that involve asset prioritization, asset request, communication, etc. Informally speaking, the responsible DM would have to coordinate the actions with other DMs, requesting the commitment of their resources and their direct participation in prosecuting the task. Given the model above, we identify the times

required to execute each subtask in the execution chain of task T_i :

- ζ_i^I - time required to identify the task; this time depends on the organization's internal processes, locations of information sensors, etc.;
- ζ_i^A - time required to determine the asset-to-task allocation;
- $\zeta_{i,j}^P$ - time required to send/route the asset P_j to the task location, including any waiting needed for asset synchronization; and
- ζ_i^E - time to attack the task ($\zeta_i^E = t_i$) – from the first asset attack to the last asset-task completion.

Therefore, the start time of a task is determined as follows:

$$s_i = b_i + \zeta_i^I + \zeta_i^A + \min_{j: y_{ij}=1} \zeta_{i,j}^P. \quad (4.1)$$

Also, note that task precedence constraints must be satisfied (that is, task execution cannot start before all its predecessors are completed). The actual processing time of a task is found as follows:

$$t_i = \min \left\{ \hat{t}_{ai}, b_i + \zeta_i^I + \zeta_i^A - s_i + \max_{j: y_{ij}=1} (\zeta_{i,j}^P + e_{j,i}) \right\} \quad (4.2)$$

From now on, we assume that the asset-to-task allocation variables $\{y_{ij}\}$ are such that

$$b_i + \zeta_i^I + \zeta_i^A - s_i + \max_{j: y_{ij}=1} (\zeta_{i,j}^P + e_{j,i}) \leq \hat{t}_{ai}.$$

This assumption does not imply that there is no resource wastage, but rather that the variables are given according to the actual asset-task processing that occurred during the mission.

The subtask time parameters defined above implicitly affect the values of task start times in human-in-the-loop experiments. In our simulation models, we assume that all tasks are identified immediately ($\zeta_i^I = 0$), and that the time required to determine the asset-to-task allocation is proportional to the number of DMs assigned to this task, but a single DM can assign the assets without any delay, i.e., $\zeta_i^A = \zeta^A \cdot \left(\sum_{m=1}^D u_{mi} - 1 \right)$. This

implies that ζ_i^A can be viewed as the time required for coordination among DMs to determine the asset-to-task

allocation. The parameter ζ^A can be viewed as coordination delay factor.

The routing time $\zeta_{i,j}^P$ depends on the distance traveled by an asset and the asset's velocity, and includes the time delay for asset synchronization (in our simulations, we assume that all assets assigned to a task must arrive at the task location and begin its execution at the same time).

4.2. Asset Utilization

The assets typically have diverse operational and execution characteristics. For example, a salient feature of single-hit weapons located on the same platform (e.g., a carrier) is the “duty cycle”, which imposes constraints on utilization of weapons of this type. Consequently, in our model, we specify a “duty cycle” time window ψ_j for each asset P_j . During a duty cycle, no asset of the same type can be committed from the same platform on which asset P_j resides.

5. Congruence Hypothesis

In order to formalize the effects of structural interactions between an organization and a mission, and to predict organizational performance, we utilize our 3-phase design methodology [8,9]. The performance of organization is obtained using the scheduling step (Phase I) of the design methodology; this step defines the processes of an organization executing the mission. In the following, we consider the notion of structure-based congruence measure derived from the following characteristics of the mission:

- Task-resource requirements;
- Task precedence/dependence; and
- Task load per resource type.

These parameters determine the (mis)match between a mission and an organization because they affect the following four primary characteristics of organizational performance:

- Accrued task gain;
- Workload balance;
- Communication requirements; and
- DM-DM dependence.

The accrued task gain measure serves as the ultimate “congru-o-meter” for assessing the fit of an organization to a mission.

In order to normatively address the congruence hypothesis, we first identify the elementary dependencies between the characteristics of mission scenario and the processes of an organization. To do so, we need to identify the features of the mission that create an incongruent situation for one organization, and a congruent one for another. In the rest of this section, we illustrate the effects of mission/task parameters on the processes of various organizations (congruent and incongruent ones) using simplified examples. In all of the examples below, we assume that the coordination delay factor $\zeta^A = 1$, asset-task processing time $e_{j,i} = 1$, task processing time window $\hat{t}_{ai} = 1$, and task release time $b_i = 0$ (all tasks appear at the beginning of the mission and are detected immediately, that is, $\zeta_i^I = 0$). Hence, task duration is fixed at $t_i = 1$, and the start time is found via:

$$s_i = \left(\sum_{m=1}^D u_{mi} - 1 \right) + \min_{j: y_{ij}=1} \zeta_{i,j}^P. \quad (5.1)$$

5.1. Resource Congruence

In this subsection, we quantify the effects of task-resource requirements on the processes of two distinct organizations.

Table 5.I. Example of asset parameters

Assets	Resource capabilities	Velocity	Locations	DM allocation	
				Organization A	Organization B
P1.1	[1,0]	1	(0,0)	1	1
P1.2	[1,0]	1	(1,1)	1	2
P2.1	[0,1]	1	(0,0)	2	1
P2.2	[0,1]	1	(1,1)	2	2

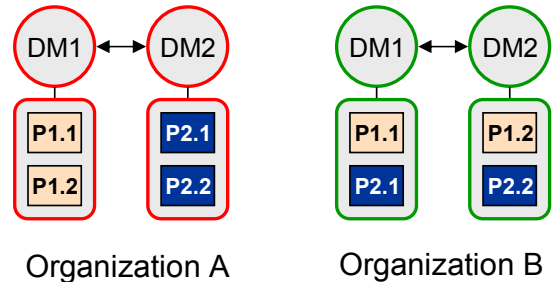


Figure 5.1. Example of Organizations

Assume that the organization consists of two decision-makers, with two platforms assigned to each (Fig. 5.1). We consider two resource types. Asset parameters (resource capabilities, velocities, locations, DM-asset allocation, etc.) are shown in Table 5.I. It is evident that the resource capabilities of DMs (according to resource

capabilities of assigned assets) are distinct for the two organizations. We define the aggregated resource capability vector of a $DM_m, m=1, \dots, D$ as $\hat{L}_m = [\hat{r}_{m1}, \dots, \hat{r}_{mL}]$, where

$$\hat{r}_{ml} = \sum_{j=1}^K a_{m,j} \cdot r_{jl}, l=1, \dots, L. \quad (5.2)$$

In Organization A, DM1 has aggregated resource capability vector of [2,0], while DM2 has aggregated resource capability vector of [0,2]. Thus, this organization has DMs with non-overlapping resource capabilities, and is termed *Functional*. In such organizations, the task execution capabilities of DMs are distinct. The DMs need to have a global view of the mission in order to execute the mission successfully.

In Organization B, each decision-maker has aggregated resource capabilities vector equal to [1,1]. This organization has DMs with maximally overlapping resource capabilities, and is termed *Divisional*. In this type of organizations, each DM has the same task execution capability as any other DM. Consequently, the mission must be divided into geographical areas, delineating areas of responsibility for each DM in order to minimize task execution conflicts.

In the following, we consider two missions that are congruent with each of the organizations, and significantly incongruent with the other. The desired mission completion time T_f is equal to 4 time units, i.e., accrued task gain is measured from 0 to 4 time units only.

A. Example S1.A: tasks with resource requirements of the same type

Consider a mission scenario (denoted by **S1.A**), consisting of two tasks, with task parameters as in Table 5.II. Each task requires the same number of resources (2), but of different types. It is evident that this scenario matches the functional Organization A. Indeed, this organization can execute both tasks with 100% accuracy without any communication delays by allocating (see Table 5.III) task T1 to assets P1.1 and P1.2 (and therefore to a single decision-maker DM1 in organization A), and task T2 to assets P2.1 and P2.2 (owned by a single decision-maker DM2 in A). The task start times for Organization A are calculated as $s_1 = s_2 = 1$ ($\zeta_i^A = 0$; see equation 5.1). Organization B must have multi-DM task processing to achieve 100% mission accuracy, with $\zeta_1^A = \zeta_2^A = 1$. The resulting task

start times are $s_1 = s_2 = 2$. On the other hand, Organization B can execute the mission with a lower accuracy and with the same task latencies as Organization A. Assigning task T1 to asset P1.1 (resources (1,0)) and task T2 to asset P2.2 (resources (0,1)), Organization B achieves accuracy of 25% for both tasks: $\alpha_1 = \alpha_2 = \left(\frac{1}{2}\right)^2 = .25$ (equation (3.10)). The task processing schedules for Organizations A and B are shown in Fig. 5.2.

Table 5.II. Example **S1.A**: task parameters

Tasks	Resource requirements	value	Locations
T1	[2,0]	1	(0,1)
T2	[0,2]	1	(1,0)

Table 5.III. Example **S1.A**: task-asset-DM allocation; accuracy 100%

Task-A					DM allocation			
					Organization A		Organization B	
tasks	P1.1	P1.2	P2.1	P2.2	DM1	DM2	DM1	DM2
T1	1	1	0	0	1	0	1	1
T2	0	0	1	1	0	1	1	1

The accrued gain function is depicted in Fig. 5.3. We can see that Organization A has a higher gain, and a higher gain area. The trade-off of accuracy versus timeliness by organization B only decreased the gain measure. Given the DM workload and gain area measures in Table 5.IV, we conclude that the Organization A is more congruent with scenario **S1.A** than Organization B.

Table 5.IV. Example **S1.A**: Organizational Measures; workload weights $W^I = W^E = 1$

organization		I(m)	E(m)	CW(m)	Θ	gain area
A, 100% accuracy	DM1	2	0	2	2	4
	DM2	2	0	2		
B, 100% accuracy	DM1	2	2	4	4	2
	DM2	2	2	4		
B, 25% accuracy	DM1	1	0	1	1	1
	DM2	1	0	1		

Table 5.V. Example **S1.B**: task parameters

Tasks	Resource requirements	value	Locations
T1	[1,1]	1	(0,1)
T2	[1,1]	1	(1,0)

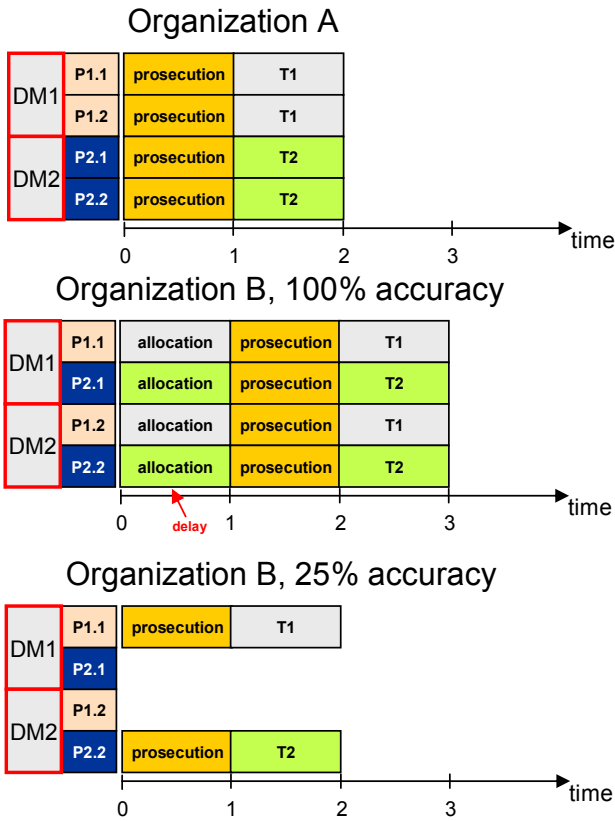


Figure 5.2. Example S1.A: Gantt-Charts

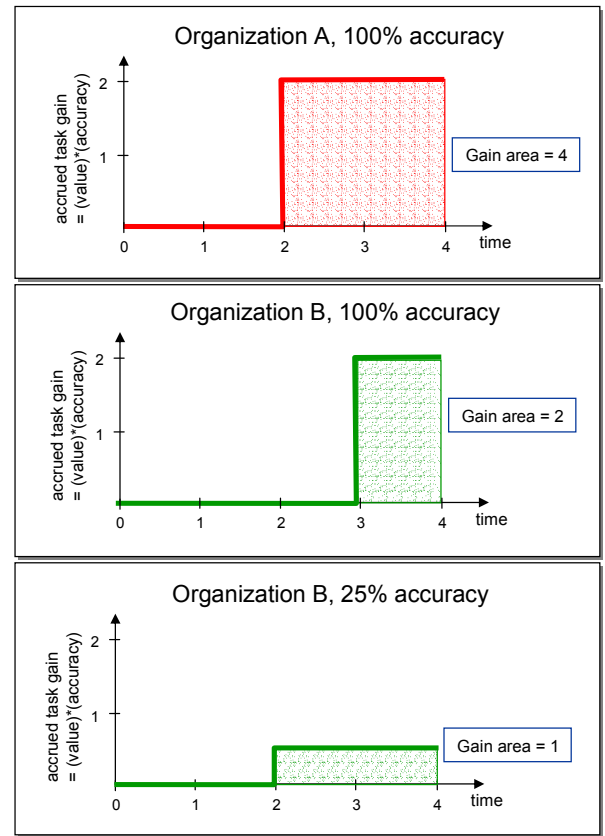


Figure 5.3. Example S1.A: Accrued Gain Plot

B. Example S1.B: tasks with resource requirements of different types

Consider a mission consisting of two tasks, with task parameters shown in Table 5.V. Each task requires the same resource vector [1,1].

Table 5.VI. Example S1.B: task-asset-DM allocation; accuracy 100%

Task-Asset Allocation					DM allocation			
					Organization A		Organization B	
tasks	P1.1	P1.2	P2.1	P2.2	DM1	DM2	DM1	DM2
T1	1	0	1	0	1	1	1	0
T2	0	1	0	1	1	1	0	1

It is evident that this resource requirement vector matches Organization B. Indeed, this organization can execute all tasks with 100% accuracy without any communication delays by allocating (see Table 5.VI) task T1 to assets P1.1 and P2.1 (and therefore to a single decision-maker DM1 in organization B), and task T2 to assets P1.2 and P2.2 (owned by a single decision-maker DM2 in B). The task start times for Organization B are

computed as $s_1 = s_2 = 1$ ($\zeta_i^A = 0$; see equation (5.1)), and the resulting Gantt-Chart is shown in Fig. 5.4.

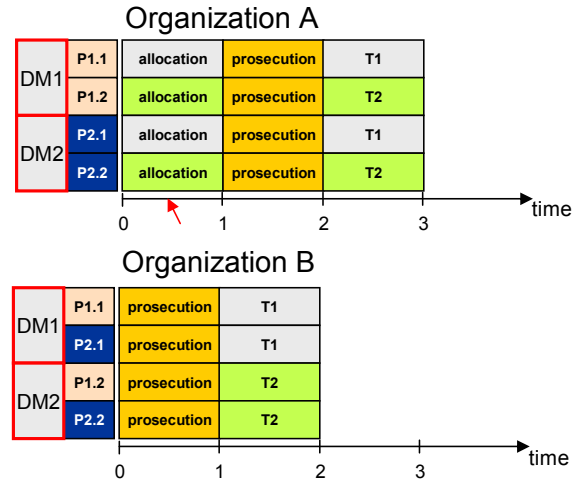


Figure 5.4. Example S1.B: Gantt-Charts; accuracy 100%

Organization A cannot avoid multi-DM task processing to achieve 100% accuracy, and, therefore, requires DM-DM communication for asset-task allocation, with $\zeta_1^A = \zeta_2^A = 1$. The resulting task start times are

$s_1 = s_2 = 2$ for executing the mission with 100% accuracy (see Fig. 5.4).

Organization A can execute the mission with a lower accuracy and the same task latencies as Organization B (see Fig. 5.5). Assigning task T1 to asset P1.1 (resources (1,0)) and task T2 to asset P2.2 (resources (0,1)), Organization A achieves accuracy of 25% for both tasks:

$$\alpha_1 = \alpha_2 = \left(\frac{1}{2}(0+1)\right)^2 = .25 \text{ (equation (3.10)).}$$

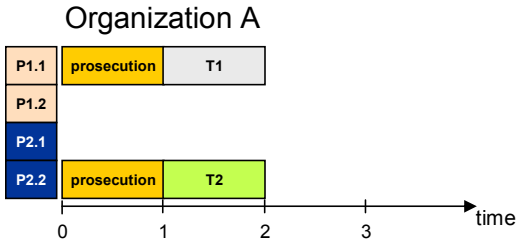


Figure 5.5. Example **S1.B**: Gantt-Chart for Organizations A; accuracy 25%

Table 5.VII. Example **S1.B**: Organizational Measures; workload weights $W^I = W^E = 1$

organization		I(m)	E(m)	CW(m)	Θ	gain area
A, 100% accuracy	DM1	2	2	4	4	2
	DM2	2	2	4		
A, 25% accuracy	DM1	1	0	1	1	1
	DM2	1	0	1		
B, 100% accuracy	DM1	2	0	2	2	4
	DM2	2	0	2		

The behavior of accrued gain functions of the organizations are reversed for scenario **S1.B** when compared to **S1.A**. We depict the measures of internal and external workload, aggregated workload and workload balance in Table 5.VII. The results show that Organization A has a higher aggregated workload than Organization B in executing the mission with 100% accuracy. The trade-off of accuracy versus timeliness by organization A only decreased the gain measure. (25% accuracy allowed Organization A to accrue a gain area of 1 with a lower workload). Note that Organization B cannot achieve the same gain with any strategy other than the one depicted in Fig. 5.4. From the workload, workload balance and gain measures, we conclude that Organization B is more congruent to scenario **S1.B** than is the Organization A. The congruence stems from a proper match of DM-resource ownership with the task-resource requirements.

5.2. Task Network Congruence

In this subsection, we quantify the effects of task precedence and inter-task information flows on organizational processes. The flows among tasks could be conceptualized as either flow of information or commodities, or the dependence of DMs that execute the tasks with precedence constraints. In either case, delays are introduced into task processing, if the dependent tasks are executed by different DMs. We assume that the desired mission completion time T_f for the scenarios considered in this subsection is equal to 5 time units. We consider a mission consisting of four tasks, with task parameters shown in Table 5.VIII, and different task graphs outlined in Fig. 5.6.

Table 5.VIII. Examples **S2**: task parameters

Tasks	Resource requirements	value	Locations
T1	[1,0]	1	(0,1)
T2	[1,0]	1	(1,0)
T3	[0,1]	1	(0,1)
T4	[0,1]	1	(1,0)

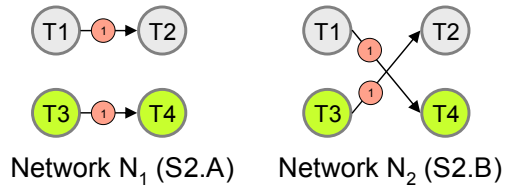


Figure 5.6. Example **S2**: Networks of Dependent Tasks

A. Example **S2.A**: dependent tasks with similar resource requirements

In this subsection, we consider the task communication network N_1 depicted in Fig. 5.6. Task-asset-DM allocations for a mission execution accuracy of 100% are shown in Table 5.IX.

Neither organization can achieve better timeliness by trading off task accuracy, because tasks require only a single resource unit. However, Organization A can avoid communication delays by efficiently assigning its assets. On the other hand, Organization B should either allow communication delay, or alternative asset allocation. The latter delays the task execution even further (since the distance to be traveled by the same asset between dependent tasks is $\sqrt{2}$; see Fig. 5.7). The resulting accrued gain plots are shown in Fig. 5.8; the workload measures and gain values are given in Table X.

Note, however, that, due to its divisional structure, the DMs in Organization B would have geographical areas of responsibility. Consequently, only one of the discussed task-asset allocations would be employed as specified by rules of engagement.

Table 5.IX. Example S2.A: task-asset-DM allocations; accuracy 100%

Task-Asset Allocation					DM allocation			
tasks	P1.1	P1.2	P2.1	P2.2	Organization A		Organization B	
					DM1	DM2	DM1	DM2
T1	1	0	0	0	1	0	1	0
T2	0	1	0	0	0	1	1	0
T3	0	0	1	0	1	0	0	1
T4	0	0	0	1	0	1	0	1

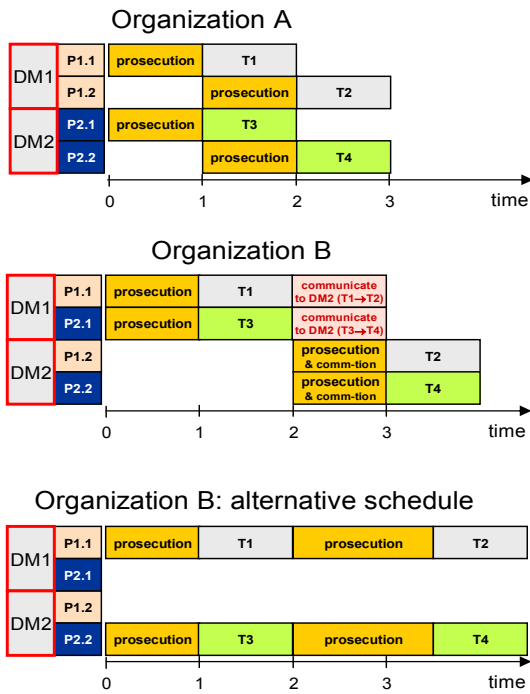


Figure 5.7. Example S2.A: Gantt-Charts

Table 5.X. Example S2.A: Organizational Measures; workload weights $W^I = W^E = 1$

organization		I(m)	E(m)	CW(m)	Θ	gain area
A	DM1	2	0	2	2	10
	DM2	2	0	2		
B	DM1	2	0	2	2	8
	DM2	2	0	2		
B, alternative schedule	DM1	2	0	2	2	7.17
	DM2	2	0	2		

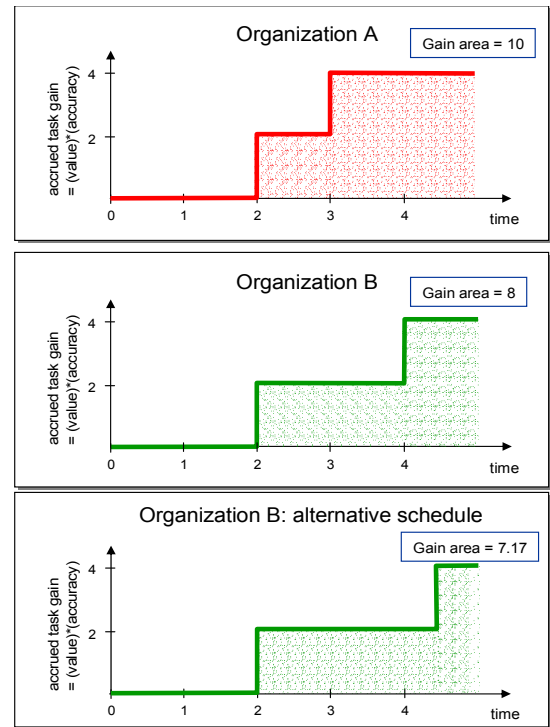


Figure 5.8. Example S2.A: Accrued Gain Plot

Table 5.XI. Example S2.B: Organizational Measures; workload weights $W^I = W^E = 1$

organization		I(m)	E(m)	CW(m)	Θ	gain area
A	DM1	2	0	2	2	8
	DM2	2	0	2		
A, alternative schedule	DM1	2	0	2	2	7.17
	DM2	2	0	2		
B	DM1	2	0	2	2	10
	DM2	2	0	2		

B. Example S2.B: dependent tasks with distinct resource requirements

For the task dependence network N_2 of Fig. 5.6, the situation is reversed. Using an approach similar to that used earlier, we obtain the workload and gain measures shown in Table 5.XI. Here, Organization B is congruent with the 4-task scenario, achieving the highest task gain with optimal workload balance.

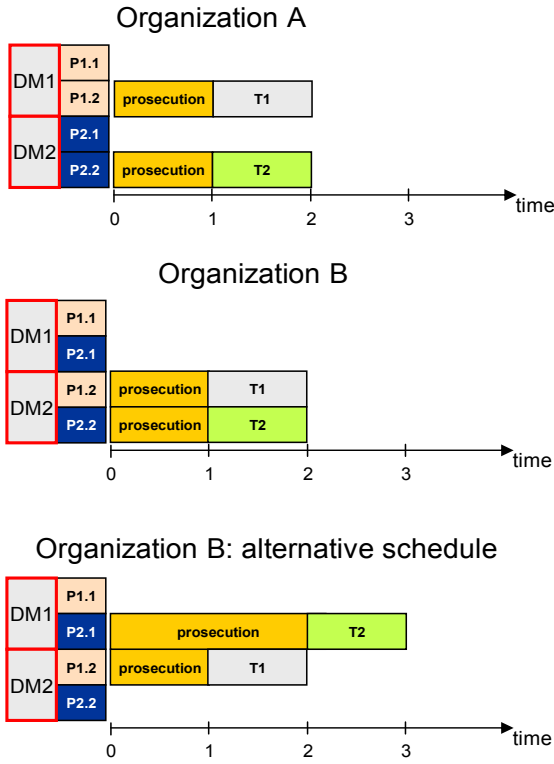


Figure 5.9. Example S3.A: Gantt-Charts

Table 5.XII. Example S3.A: task parameters

Tasks	Resource requirements	value	Locations
T1	[1,0]	1	(2,1)
T2	[0,1]	1	(2,1)

Table 5.XIII. Example S3.A: Organizational Measures;
workload weights $W^I = W^E = 1$

organization		I(m)	E(m)	CW(m)	Θ	gain area
A, 100% accuracy	DM1	1	0	1	1	4
	DM2	1	0	1		
B	DM1	0	0	0	1.414	4
	DM2	2	0	2		
B, alternative schedule	DM1	1	0	1	1	3
	DM2	1	0	1		

5.3. Congruence Based on Workload Balance

In this section, we explore the effects of workload imbalance in either functional resources or geographic areas of responsibility on the processes of Organizations A and B. In the scenarios below, the

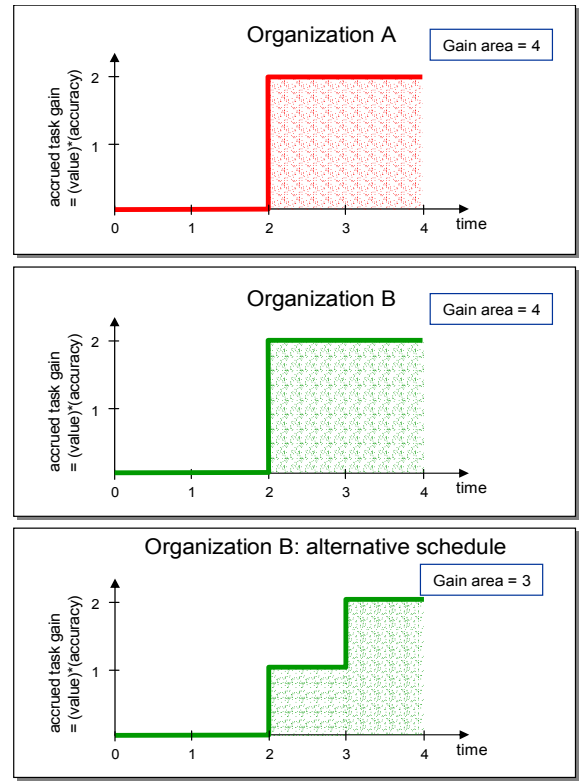


Figure 5.10. Example S3.A: Accrued Gain Plot

desired mission completion time T_f is equal to 4 time units.

A. Example S3.A: geographical area imbalance

Let the scenario consist of two tasks with task attributes as shown in Table 5.XII. The mission scenario is such that it loads the area closest to the assets allocated to DM2 in Organization B. Note that there exists an alternative assignment of assets to tasks as shown in Fig. 5.9, but it has deleterious effect on the accrued task gain (Fig. 5.10). Thus, in this case, there is a single optimal asset-task allocation for Organization A, while there are two alternative allocations for Organization B: one allows it to achieve a higher gain over time while resulting in imbalanced workload, and the other allows it to balance the workload with a delayed accrual of task gain (Table 5.XIII). Evidently, Organization A is more congruent with this mission than is Organization B.

B. Example S3.B: functional area imbalance

Let the scenario consist of two tasks with task attributes as in Table 5.XIV. For this scenario, assume that there are no task communication or dependence delays (see Fig. 5.11). Consequently, the total gain (assuming ideal DM performance) is the same for both Organizations A and B. However, Organization B performs this mission by

allocating tasks to different DMs (workload is distributed), while organization A has to assign these tasks to the same DM, thus increasing its workload. As a result, the workload imbalance (41% higher than that in Organization B; see Table 5.XIII) is higher for organization A, indicating that it is incongruent for this scenario.

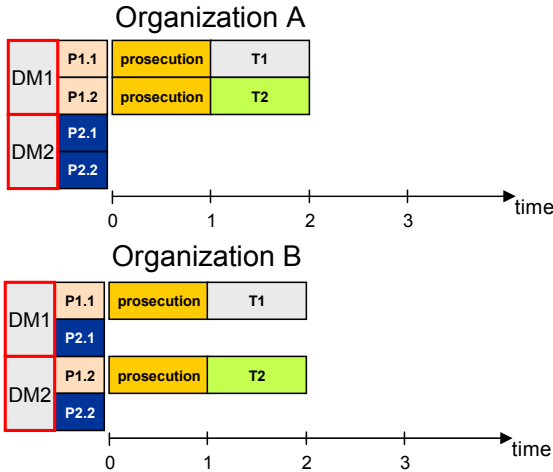


Figure 5.11. Example S3.B: Gantt-Charts for Organizations A and B; accuracy 100%

Table 5.XIV. Example S3.B: task parameters

Tasks	Resource requirements	value	Locations
T1	[1,0]	1	(0,1)
T2	[1,0]	1	(1,0)

Table 5.XV. Example S3.B: Organizational Measures; workload weights $W^I = W^E = 1$

organization		I(m)	E(m)	CW(m)	Θ	gain area
A	DM1	2	0	2	1.41	2
	DM2	0	0	0		
B	DM1	1	0	1	1	2
	DM2	1	0	1		

6. Methodology for Experiment-8

In order to test and validate our hypothesis that the better an organization is matched to its mission, the better will that organization perform, we designed an experiment to be conducted at NPS using the DDD team-in-the-loop simulator [6]. Instead of modeling an organization to execute a specified mission [8,9], we used a “reverse engineering” approach of designing mission scenarios that specifically (mis)matched selected organizational structures. The concepts

developed in [8,9] for modeling DM-resource allocation (Phase II) were used to create matches and mismatches between task-resource requirements and DM-resource capabilities by manipulating the need for multi-DM task processing (reducing the need for multi-DM processing in congruent cases, and increasing it in the incongruent ones). Multi-DM task processing requires communication and asset synchronization among the DMs participating in task execution, thus increasing task execution latency. Based on our scheduling algorithms (Phase I of our design process), we can further increase the DM-DM dependence in incongruent cases by specifying a precedence structure among tasks that must be executed by different DMs. Thus, task latencies at a single DM greatly affect the overall performance of the team. The results for simple congruent and incongruent situations, discussed in Section 5, provided the theoretical insights for the design of A2C2 Experiment 8.

To effectively test our congruence concepts empirically, the “distance” between the two organizational structures should be maximized to counter the inevitable experimental variance when dealing with human teams. The A2C2 experimenters preselected *functional* (F) and *divisional* (D) organizational structures. These architectures (Table 6.I) represent two extreme cases of organizational structures, and therefore are suited for congruence analysis. Two scenarios, termed *functional* (f) and *divisional* (d), were designed to create the matched situations for Ff (functional structure – functional scenario) and Dd (divisional organization and divisional scenario) cases, and to create mismatches for Fd and Df cases. The human-in-the-loop experiment was conducted using 8 teams, and is described in a companion paper [7].

Table 6.I. Generic Characteristics of Functional and Divisional Organizations

Divisional	Functional
One DM controls multiple types of resources	One DM controls a single resource type
DMs have general knowledge about resources	DMs have more specialized knowledge about the resources they control
DM controls all the resources on an asset carrier	DM controls resources across asset carriers

The descriptions of designs for f and d mission scenarios and outlines of parameters for F and D organizations can be found in a companion paper [7]. The actual scenario designs have been developed in close cooperation between NPS and UConn, with UConn providing normative mission scenarios and organizational design, and NPS developing the actual DDD scenarios with realistic task models and specifications (Fig. 6.1).

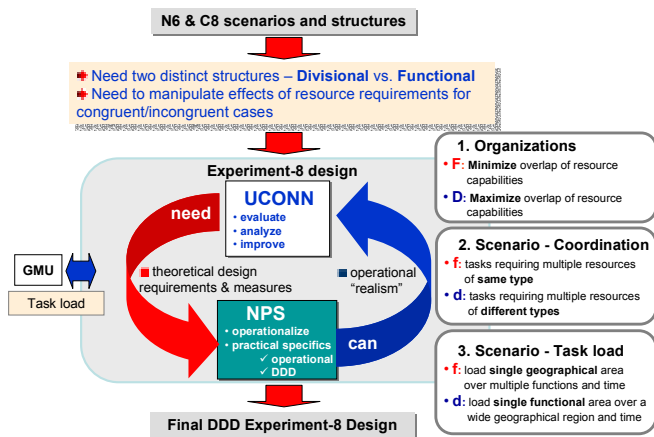


Figure 6.1. Experiment-8 Design Modeling Cycle

7. Predictions versus Experimental Results

We compared the analytical predictions with empirical data from the human-in-the-loop experiment using similar measures, including the total *accrued task gain* (based on the task scoring method, and identifying the trade-off between task latency and task accuracy), *gain area*, *number of DM-DM assists* (needed for multi-DM task processing, and termed *external coordination* in the 3-phase design process), and total workload distribution measure. Measures from the DDD simulations were extracted using the new DDD Post Processor [12].

In the rest of this section, we compare the pre-experiment normative predictions obtained by the ORGDESIGN software [13]. The results of applying Phase I (scheduling) of organizational design process to experimental scenarios and organizations, and those of human-in-the-loop experiment conducted at NPS [7], [3], [4] are compared. The data is extracted for time-

critical tasks only, which include the mission tasks and attack-defend tasks, as indicated by commander's intent. For complete experiment results, see companion papers [3], [4].

Predicted results are based on the model for which the 100% accuracy is required and platform allocation delay (when asset request is needed) is equal to $\zeta^A = 50$ sec. The empirical data are averaged over all teams performing the corresponding organization-mission pair (see [7]). The mission time was $T_f = 2100$ sec for each scenario.

7.1. Scenario f

Scenario **f**, designed to be congruent with organization **F** and incongruent with organization **D**, contained tasks similar to those in Examples S1.A, S2.A, and S3.A (Section 5), but with realistic resource requirements.

The results for accrued task gain are shown in Fig. 7.1. We can see that congruent organization (**F**) outperforms the incongruent one (**D**, dotted line). The disparity of actual pattern of accrued gain over time is attributed to the task execution time, which varies according to the task allocation/scheduling strategies employed by the normative organization and human teams. Also, the simulated model uses simplistic assumptions of fixed coordination (asset request) time, and does not allow the timeliness/accuracy tradeoff (100% accuracy is required).

The total aggregated accrued gain is higher in normative organizations due to the above restrictions of the ORGDESIGN model, as well as the assumption of an ideal agent model that does not account for effects of accrued workload on DM performance.

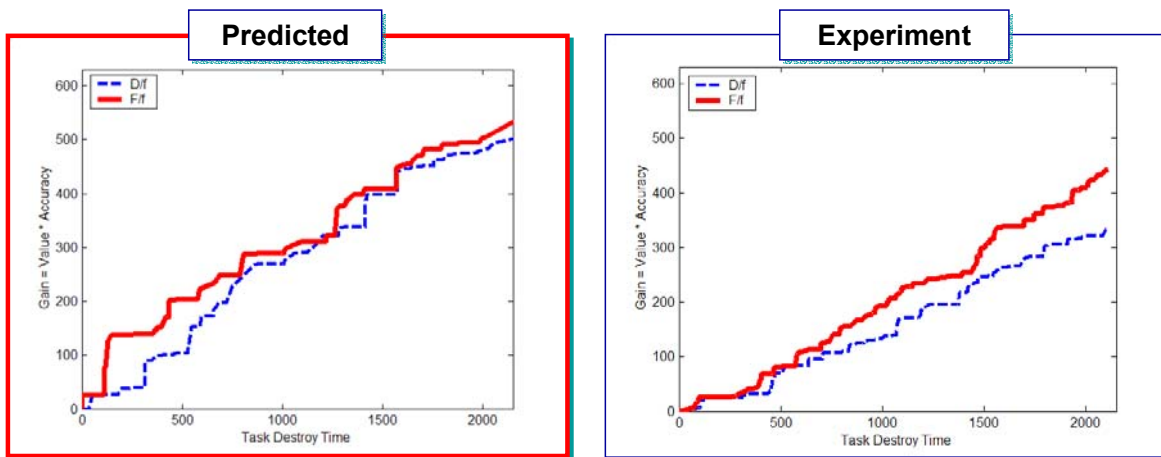


Figure 7.1. Gain plot for Time-critical tasks: Scenario **f**

The gain accrued by the human team strongly depends on the accuracy-timeliness trade-offs employed by human agents during the mission. Although the predicted value of total accrued gain was higher than the one achieved by human teams in the experiment, the overall difference in gain area, which identifies the congruence difference between organizations **F** and **D** on mission **f**, was higher in experimental data (see Fig. 7.2). The difference in gain areas between the congruent (**F**) and incongruent (**D**) organizations for scenario **f**, computed via $\Delta = \frac{A(\mathbf{F}, \mathbf{f}; T_f) - A(\mathbf{D}, \mathbf{f}; T_f)}{A(\mathbf{F}, \mathbf{f}; T_f)}$,

was predicted to be 8.7%, but was observed to be 21.7% in Experiment 8. This is due to the fact that the effects of coordination were more prominent in the experiment.

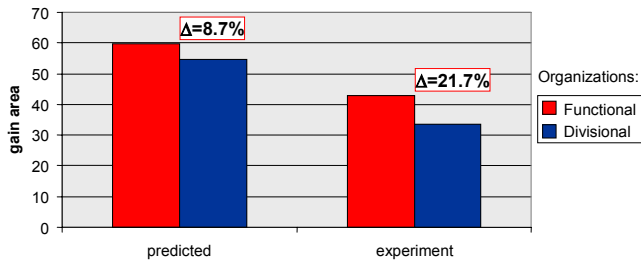


Figure 7.2. Gain Area Measure: Scenario **f**

The incongruent organization tried to adapt by sacrificing the accuracy (instantaneous task gain) in order to achieve the mission faster. Fig. 7.3 provides the insight in the congruence characterization: the

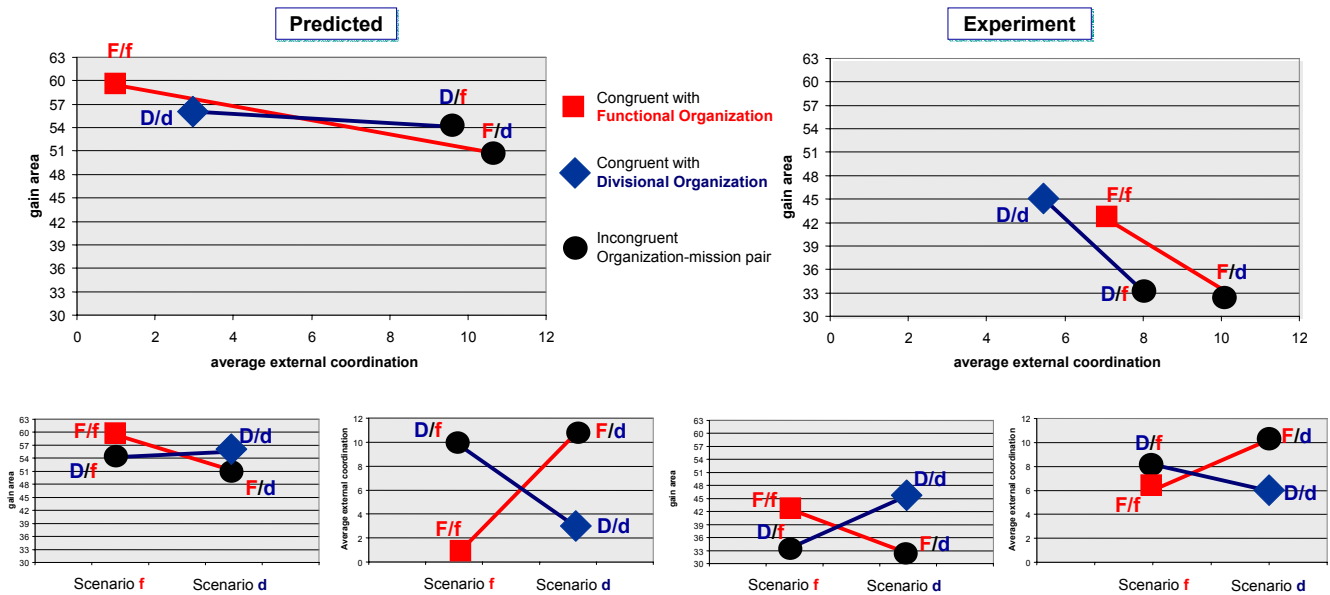


Figure 7.3. External Coordination versus Gain Area

congruent organization achieves a higher gain area (higher mission tempo). Indeed, it executes the mission with a lower external coordination (higher speed of command – lower number of DM-DM assists). Consequently, the congruent organization executes the mission with higher independence of DMs and lower cognitive load for mission execution. In this figure, we show the average external coordination per DM.

Given that organization **F** achieves a higher gain with lower coordination load than organization **D**, we conclude that it is more congruent than the latter to mission scenario **f**. Our models predicted the pattern of incongruence in organization **D**: incongruence was due to mismatches between the resource capabilities of DMs in **D** and the resource requirements of tasks in scenario **f**. These mismatches were modeled by having tasks that required multiple resources of the same type, as well as time-loading of geographical areas over time.

7.2. Scenario **d**

Scenario **d**, designed to be congruent with organization **D**, and incongruent with organization **F**, contained tasks that are similar to those in Examples S1.B, S2.B, and S3.B (Section 5), but with realistic resource requirements.

The normative and experimental accrued task gains are shown in Fig. 7.4. We can see that congruent organization (**D**, dotted line) outperforms the incongruent one (**F**). The disparity in actual pattern of accrued gain over time is attributed to the same modeling constraints as in scenario **f** (see Section 7.1).

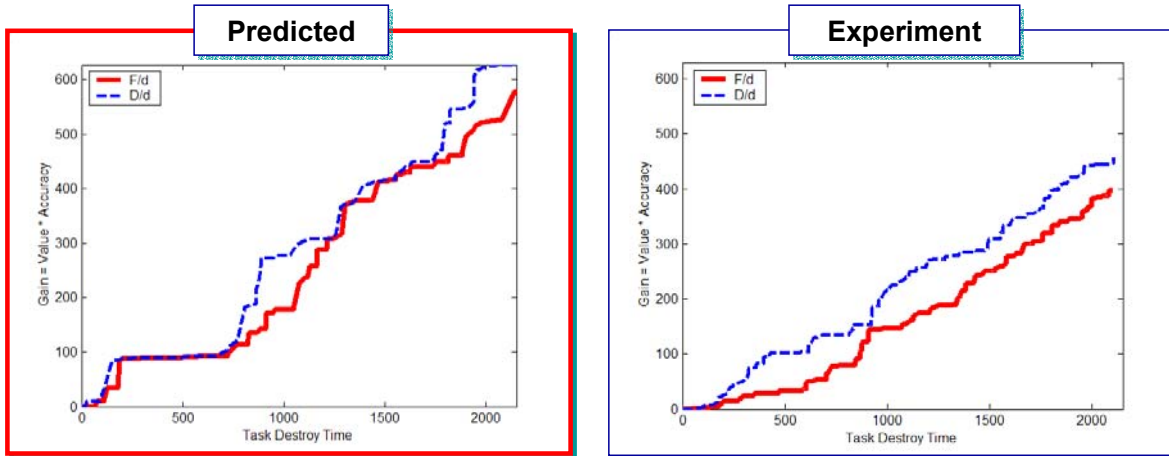


Figure 7.4. Gain plot for Time-critical tasks: Scenario **d**

The total aggregated accrued gain is higher in normative organizations due to these restrictions of the ORGDESIGN model. Although the predicted value of total accrued gain was higher than the one achieved by human teams in the experiment, the overall differences in gain area, which identifies the congruence difference between organizations **F** and **D** on mission **d**, was higher in experimental data (see Fig. 7.5). The difference in gain areas between the congruent (**D**) and incongruent (**F**) organizations for scenario **d**, computed via $\Delta = \frac{A(\mathbf{D}, \mathbf{d}; T_f) - A(\mathbf{F}, \mathbf{d}; T_f)}{A(\mathbf{D}, \mathbf{d}; T_f)}$, was predicted to be

9.8%, but was observed to be 39.6% in Experiment 8. The effects of modeled coordination and multi-DM task processing have been even more pronounced in this scenario. This is due to the fact that multi-resource tasks (scenario **d**) force the multi-DM task processing in incongruent organization **F** (since there is very little overlap between resource capabilities of DMs in this organization), whereas tasks that require multiple resources of the same type (scenario **f**) do not necessarily require multi-DM task processing in incongruent organization **D**, since each DM possesses multiple resource capabilities of single type. The multi-DM task processing is achieved in this case from constraints on the resource utilization (weapon duty-cycle prohibits the simultaneous use of assets with the same resource type located on a single platform) and task processing (tasks have a processing time window).

Given that organization **D** achieves a higher gain with lower coordination load than organization **F**, we conclude that it is more congruent than the latter to

mission scenario **d**. Our models predicted the pattern of incongruence in organization **F**, which was due to mismatches between the resource capabilities of DMs in **F** and the resource requirements of tasks in scenario **d**. These mismatches were modeled through tasks that required resources of different types, as well as time-loading of functional areas over time.

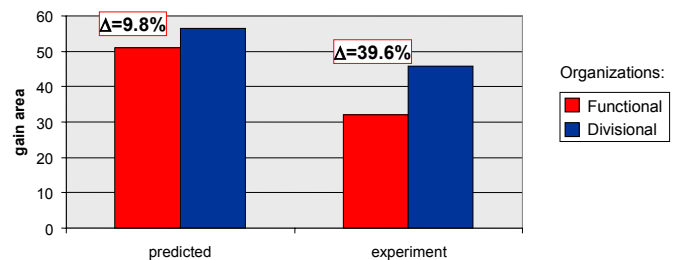


Figure 7.5. Gain Area Measure: Scenario **d**

8. Conclusions and Future Extensions

In this paper, we defined structure-based congruence measures by evaluating the closeness of task parameters with the organizational structure and processes. In order to validate the normative predictions, namely that structure-based congruence leads to performance-based congruence, we designed and conducted a team-in-the-loop A2C2 experiment using two different organizational structures and two different missions. In this paper, we described how we reverse-engineered missions to generate mismatches with organizations, and how we modeled the specific structural mismatches and matches among the corresponding elements of organizations and missions.

The model served as the basis for our structure-based congruence framework.

In our experiments, we found that the model-predicted structural mismatch between an organization and a mission indeed resulted in degraded performance in the non-congruent cases when compared to the congruent ones – specifically in terms of timeliness of task execution, coordination workload, and the total gain attained by the organization. We found that the congruent organization achieves a higher gain area (higher mission tempo) while executing the mission with lower external coordination (higher speed of command – lower number of DM-DM assists) and, as a result, higher independence of DMs and lower cognitive load for mission execution.

The analytic methods, applications, and measures illustrated in the paper form the basis for current research on organizational design and adaptation for large-scale human-machine systems. Although our normative models predicted the overall performance trend, the disparity between the predicted and experimental performance is due to the limited nature of our organizational models, as well as inherent nature of humans to make trade-offs among team objectives in executing the mission. Such trade-offs were not allowed in our models, and ideal agent models were employed. In our modeling, all tasks must be executed with 100% accuracy, and a fixed coordination delay model was utilized. In spite of these limitations, the model predicted the observed trends very well. Investigating the agent models with cognitive biases and human limitations, different task priorities and limited look-ahead decision-rules, as well as exploring other dependent variables that describe organizational processes, would constitute the next step in our modeling process.

References.

[1] Burton, R.M., and B. Obel, *Strategic Organizational Diagnosis and Design: Developing Theory for Application*, (2nd Ed.). Boston, MA: Kluwer Academic Publishers, 1998.

[2] Cameron, K.S., “Effectiveness as paradox: consensus and conflict in conceptions of organizational effectiveness”, *Management Science*, Vol. 32, No. 5, 539-553, 1986.

[3] Diedrich, F., E. Entin, S. Hutchins, S. Hocevar, B. Rubineau, and J. MacMillan, “When Do Organizations Need to Change – Part I: Coping with Organizational Incongruence”, to appear in *International Command and Control Research and Technology Symposium*, Washington, DC, June, 2003.

[4] Entin, E., F. Diedrich, D. Kleinman, B. Kemple, S. Hocevar, B. Rubineau, and D. Serfaty, “When Do Organizations Need to Change – Part II: Incongruence in Action”, to appear in *International Command and Control Research and Technology Symposium*, Washington, DC, June, 2003.

[5] Hollenbeck, J.R., H. Moon, A. Ellis, B. West, D.R. Ilgen, L. Sheppard, C.O. Porter and J.A. Wagner, “Structural Contingency Theory and Individual Differences: Examination of External and Internal Person-team Fit,” *Journal of Applied Psychology*, Vol. 87, pp. 599-606, 2002.

[6] Kleinman, D. L., P. Young, and G. S. Higgins, “The DDD-III: A Tool For Empirical research in Adaptive Organizations”, *Proceedings of the 1996 Command and Control Research and Technology Symposium*, Monterey, CA, June, 1996.

[7] Kleinman, D.L., G.M. Levchuk, S.G. Hutchins, and W.G. Kemple, “Scenario Design for the Empirical Testing of Organizational Congruence”, to appear in *International Command and Control Research and Technology Symposium*, Washington, DC, June, 2003.

[8] Levchuk, G.M., Y. N. Levchuk, Jie Luo, Krishna R. Pattipati, and David L. Kleinman. (2002a). “Normative Design of Organizations - part I: Mission Planning”, in *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 32, No. 3, May 2002, pp. 346-359.

[9] Levchuk, G.M., Y. N. Levchuk, Jie Luo, Krishna R. Pattipati, and David L. Kleinman, “Normative Design of Organizations - part II: Organizational Structure”, in *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 32, No. 3, pp. 360-375, May 2002.

[10] Mackenzie, K.D. *Organizational Design: The Organizational Audit and Analysis Technology*, Alex Pub. Co., Norwood, New Jersey, 1986.

[11] Mackenzie, C.F., N.J. Jefferies, W.A. Hunter, W.N. Bernhard, Y. Xiao, and R. Horst, “Comparison of self reporting of deficiencies in airway management with video analysis of actual performance”, *Human Factors*, 38(4), pp. 623-635, 1996.

[12] Wong, A., and D. Kleinman, *DDD Post Processor V1.2 User Guide*, Technical Report, Naval Postgraduate School, Oct 4, 2002.

[13] <http://moody.engr.uconn.edu/cyberlab>, Organizational Design Software Environment (ORGDESIGN), *University of Connecticut, Dept. of Electrical and Computer Engineering, CyberLab*, 2003.