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Modeling and Agent-Based Simulation of Organization in a Stochastic Environment

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Abstract

This paper describes a generic model and agent-based simulation to facilitate the analysis of interplay of information collection (task identification) and decision making (task execution) processes, as well as the information flow behaviours in organizations in the face of stochastic mission environments. In these mission environments, task arrivals are stochastic, the characteristics of tasks are not known a priori, but maybe inferred to a certain degree by undertaking the information collection or task identification processes. Through the information collection processes, the organization collects the relevant attributes of tasks to estimate the resources necessary for their execution. This information is then used to allocate resources effectively for the execution of tasks.

Our model, following structural contingency theory, depicts an organization as consisting of an information-processing, communication and coordination structure that is designed to achieve a specific set of goals, and is comprised of individuals with different information collecting and task execution capabilities. We develop a simulation toolkit based on a discrete event simulator, specifically the $ANYLOGIC^{®}$ simulation package, to quantify the performance of an organization based on this model. We illustrate our approach using a number of coordinating organizational structures operating in a stochastic mission environment.

I. Introduction

Simulation modeling in context of computational analysis of organizations has been a prominent approach in social science research. Organizational engineering is the process of configuring an organizational structure to accomplish a given high level task (termed a mission), while attempting to satisfy the stated performance objectives. An organization includes people supported by information-processing and communication tools [1], [2].

Over the past forty years, simulation has become a primary tool for decision-making in engineering design (e.g., complex systems) and in discrete-event logistics systems (e.g., warehousing, manufacturing, and supply chains). Ostensibly, simulation models accomplish two valuable objectives: 1) they reveal, in a controlled way, the effects of interacting dynamics in complex systems, and 2) they create ”synthetic histories”, which may reflect the impact of uncertainties in the occurrence of future events, for example, the task demand. These synthetic histories can be studied to assess the impact of system design decisions, policies, decision algorithms, or ad hoc interventions. Because simulations are computational devices, many different synthetic histories, with different realizations of random processes, can be created, enabling quantitative risk assessment [3].

In many fields, including engineering, management and organizational science, simulations based on computational organization theory have been used to: (i) provide insight into the degree of match between the tasks and organizational structures, (ii) quantify how people, work processes and organizational structure influence the performance of tasks, (iii) identify bottlenecks, and (iv) improve the quality and efficiency of an organization [4]. Organizational simulation also provides an enabling toolkit for people to view, analyze, and to understand a current organization through interactive simulation, model the changes to an organization resulting from design and policy modifications and updates, and ascertain in a synthetic environment the intended and unintended effects of these changes.

Organizations rely on information for making decisions, controlling tasks and coordinating interrelated activities. Thus, the behavior and quality of information processes which collect this information would directly influence the quality of information and hence performance of the organization. The stochastic environment under this study embodies mission environments where tasks' attributes are not certain, information related to the tasks needs to be collected and analyzed before detailed actions for task execution can be applied. This paper provides a generic computational model and a simulation kit for information collection and task execution in organizations in the face of such uncertain mission environments.

Our model, following structural contingency theory, depicts an organization as consisting of an information-processing and communication structure that is designed to achieve a specific set of goals, and is comprised of individuals with limited capacity. The mission is composed of a set of stochastic and dynamic tasks, with possible interdependencies encoded in a directed acyclic task graph. The identification and execution phases of a task are decomposed into lower level sub-tasks, i.e., identification sub-tasks and execution sub-task. We model the identification phase of a task as a process of applying certain resources to identify the hidden attributes of the task. When the relevant attributes of a task are identified, its execution requirements can be inferred with a higher degree of certainty. The execution phase of a task requires the allocation of resources for successful task completion.

The communication and coordination structure of the organization is encoded by a network, termed the coordination network. The nodes of the network represent agents and organizational repositories, and edges of the network denote direct communication channels among the network nodes.

To simulate the behavior of an organization working in an uncertain environment with a concrete objective, we implement the mission environment and the organization model using a discrete event simulator, specifically, $ANYLOGIC^{®}$ [5]. We illustrate how the model implementation can be used to provide organization designers insights into general organizational behavior, performance and information flows.

The rest of the paper is organized as follows: In section II, our organizational model is presented, which includes the task model and the organization structure. Section III provides an example simulation environment, and several organizations of interest for illustrative purposes. Section IV concludes the paper and offers future research directions.

II. Organizational model

The organizational components are comprised of the resources, tasks and organization structure.

A. Resources

We model the physical assets as well as the knowledge, expertise and information necessary for the processing of tasks as resources. A resource is denoted by $r_k = (r_{ck}, r_{qk}, r_{tk})$, $k = 1, ..., n_r$. Here r_{ck} is the resource type identifier, r_{qk} is the quantity, and r_{tk} is the transferability indicator of the resource r_k. n_r is the number of types of resources in the system. If the transferability indicator is true, it implies that resource r_k can be transferred to other agents and/or organizational repositories through communication.

B. Tasks

The work activities of the organization are denoted as tasks. A task is an activity that entails the use of relevant resources and is performed by an individual agent or a group of agents to accomplish the mission objectives. Every task in itself represents a “small mission”. Workflows, dependencies, and input-output relationships among tasks are encoded in a directed, acyclic graph, termed the task graph. The relationships among tasks considered in our model are ’enable’, where a task cannot begin until all its enabling tasks are completed.

Each task T_i is characterized by the following parameters for its execution:

- Required resources, $Resource_R(T_i) = \{r_{ik}\}_{k=1}^{n_r}$, r_{ik} denotes the amount of resource type r_k that task t_i needs;
- Baseline expected execution time $\overline{PT}(T_i)$;
- Baseline workload per unit time: $\overline{UWL}(T_i)$;
- Execution consequence set, which can include:
  - Identified processing parameters of tasks, i.e., the target tasks’ required resources for execution, execution time, and unit workload, etc.;
  - Resources gained by an acting agent during the task execution; these resources can be either transferable or non-transferable, $Resource_G(T_i) \subseteq R$;
  - A value, $Val(T_i)$, indicating the relative importance of the task in the mission.

Tasks requiring simple identification can be decomposed into two sequential tasks according to our modeling, as in Fig.1(a), where sub-task A denotes the identification phase and sub-task B represents the execution phase. Before the execution of sub-task A, processing parameters of task B are unknown, whereas when sub-task A (task identification) is completed, the processing details of sub-task B are revealed. Tasks needing elaborate identification, where multiple identification sub-tasks are necessary, can be decomposed into a sub-task graph. For example, in Fig. 1(b), we have a high level task requiring the parallel identification of attributes $C1$, $C2$ and $C3$. Here, three identification sub-tasks $A1$, $A2$ and $A3$ enable a dummy sub-task $A4$, which requires no execution resources or workload, but has the execution consequence of setting the processing parameters of task B.

C. Organization

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. Our model of the coordination network representing an organization is composed of:

- Agents and organizational repositories as the nodes;

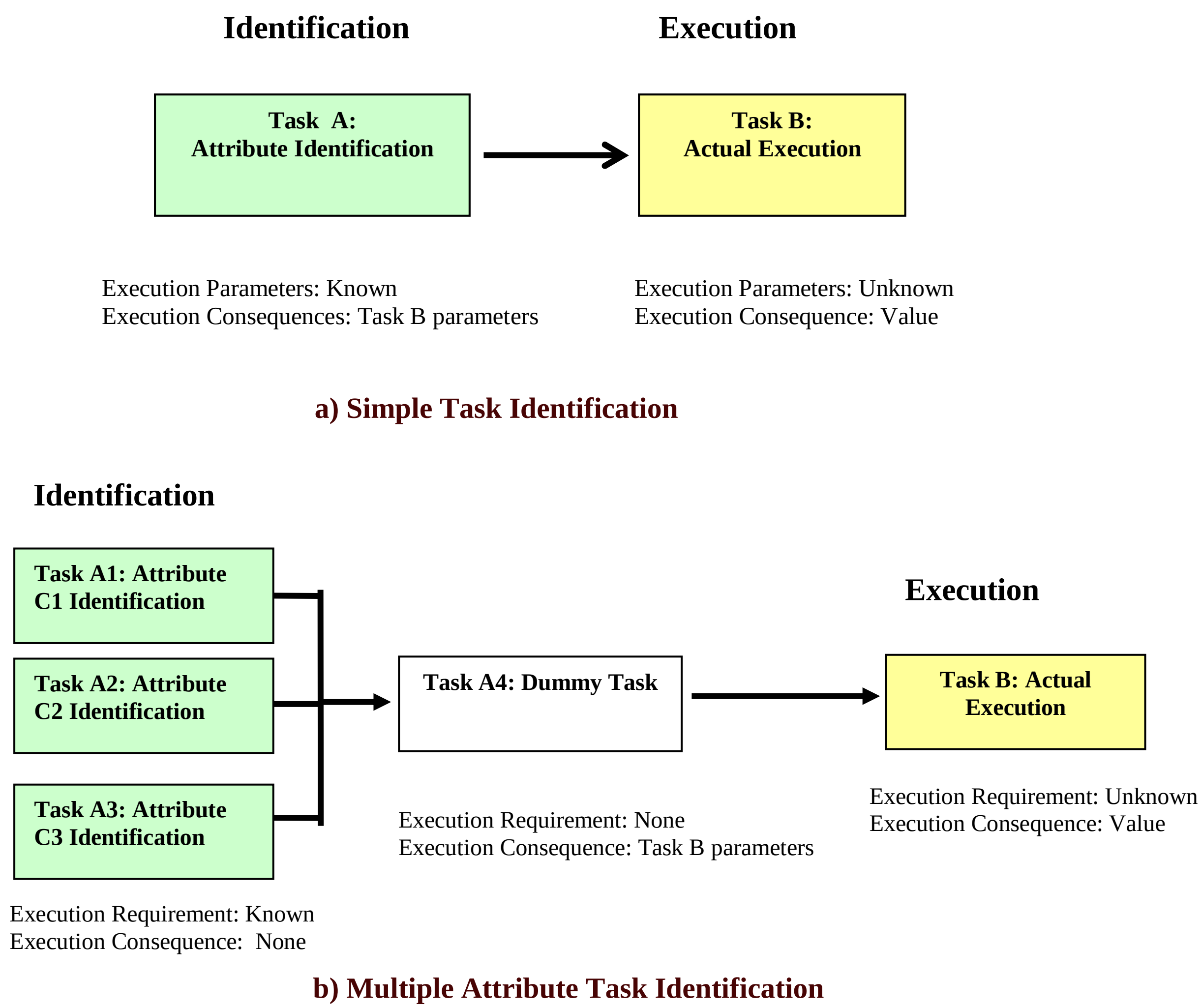

Fig. 1. Task decomposition example

- Communication links between agents and/or organizational repositories as the edges. The nodes and edges form the paths along which information are shared and resources are transferred;
- Coordination groups which consist of subsets of nodes and the internal edges among these nodes. These denote groups of agents and repositories, which can directly coordinate their resources and exchange information among them for task execution.

Agents are automated systems representing human decision makers in the system. Organizational repositories are where resources, tasks' status and information can be stored and retrieved. An illustrative organizational structure is shown in Fig. 2.

1) Agents: Agents, or human decision makers, engage in the activities of an organization, by virtue of their task execution and their positions in the communication and coordination structure of the organization.

In general, agents are provided with limited resources with which to accomplish their objectives. Agents,

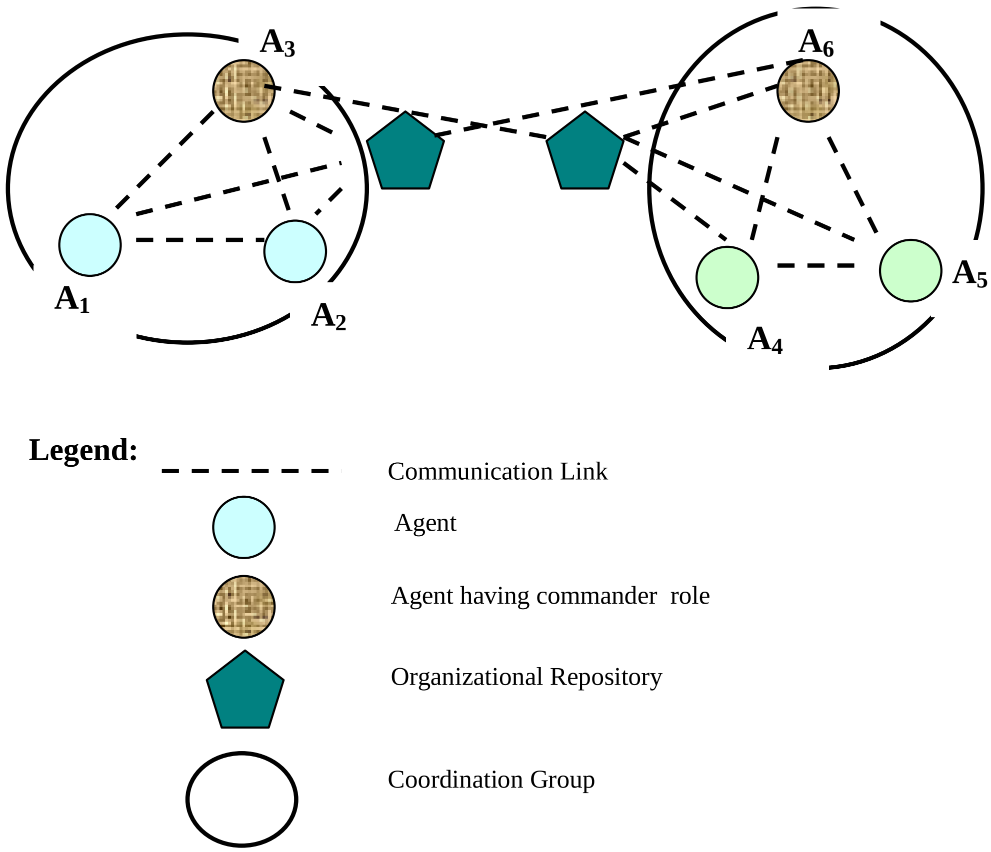

Fig. 2. Communication and Coordination Structure Example

representing human decision makers, have workload constraints. Task identification, execution, communication and coordination efforts all account for an agent's workload. The distribution of these resources among the agents, the assignment of an agent's resources to tasks, and the coordination strategy of the agents for task execution are the key elements in the design of an organization.

The characteristics of an agent, A_j, include:

- Ownership of resources, $Resources(A_j) \subseteq R$; the agent can either own these resources a priori, or can acquire them as a result of executing a task, or obtain them from the resource repository;
- Maximum workload, $Max\_UWL(A_j)$. We assume that, at any time, the workload of an agent cannot exceed its maximum workload;

2) Organizational repositories: These are the modeling entities for local information and transferable resources among coordinating agents.

The items in a repository include:

- Transferable resources;
- Configuration information of the mission and the organization, such as the mission task graph and the resource

capabilities of agents;

- Run-time information, such as identified task parameters, task status, and agents' workload. This information is stored and may be retrieved by the agents directly connected to the repository;
- History records, which include the assignment of agents' resources to tasks and the communication and coordination activities, etc.

The configuration of connections among agents and repositories can model various organizational structures of interest. One extreme organization, where every decision maker is isolated and has own goals, has one to one agent-repository relationship, and there is no connection between any two repositories; the other extreme organization is that everyone in the organization can share the resources and information directly. Here, the organization has the structure that all agents are connected to one single repository. Real-world organizations, where agents can share part of the organizational resources and information, are somewhere in between these two extremes.

3) Agent Behavior Model: We utilize the concept of an intelligent synthetic agent as a computational system that is situated in the task environment, and is capable of flexible autonomous actions in this environment. The agent employs the following processing stages: environment sensing, information processing, and action selection [6]. The environment sensing activities are for situation awareness of the agent; these are modeled as communications between an agent and his directly connected repositories which provide the agent with local static and runtime information. Information processing activities include communication and coordination to decide which task to execute, when, and with which resources from which agents. The action selection phase corresponds to the monitoring activities during task execution.

Agents can assume two different roles in the organization, namely, coordinator and executor. Coordinators are those agents who proactively coordinate with executors in the local coordination group as well as directly connected coordinators of other coordination groups for environment sensing and information processing; and executors are the agents who cooperate with the coordinator and peer executors in the processing of tasks.

D. Information Flow Analysis and Performance Measures

The interdependencies among the components and the behavior of the agents in the organization are major determinants of the performance of an organization. Specifically, we collect measures related to information processing and coordination as follows:

- statistics of task completion with the help of agent collaboration (resource coordination) and/or information sharing, i.e., number of tasks completed, the average elapsed time from task appears to the time the task is identified/executed, the rate of task disappearance without being processed;
- resource transfer statistics, i.e., the rate of resource transfer, the average number of nodes a resource traverse

during the transfer, etc;

- statistics of tasks completed by agents sharing information;
- workload of information sharing imposed on the agents.

We consider the following general metrics to evaluate organizational performance:

- mission completion factors, i.e., whether the mission tasks are all finished, the ratio of the tasks identified to tasks appeared, the ratio of tasks executed to tasks identified, etc.;
- distribution of workload among the agents; and for each decision maker, the distribution of the workload among information collection, task execution and coordination activities.

III. An Experiment System

We use the discrete event simulator encapsulated in the $ANYLOGIC^{\circledR}$ software package to implement the organization model described in sections II. $ANYLOGIC^{\circledR}$ enables faster model creation, extension, and reusability.

In our experiment simulation, we consider an organization (Fig. 3) of 4 decision makers, namely, agents A1, A2, A3 and A4. Here, A1 and A2 form GroupA, and A3 and A4 form GroupB. RepositoryA and RepositoryB represent the information repositories of GroupA and GroupB, respectively.

The mission environment, conforming to the modeling blocks defined in the previous section, is modeled as a set of mission tasks with inter-task dependency encoded via a task graph and a set of independent, time-critical tasks. The mission task graph structure is known to the organization, whereas processing requirements and the parameters of the tasks may be unknown in advance. This information may be inferred at the end of the task identification phase. When a task is identified by a group, the processing requirements for the execution of the task become known to all the agents in the group. This information remains unknown to the agents in the other groups, unless there is communication among the groups for sharing information. The presence and processing parameters of time-critical tasks, representing dynamic and unpredictable tasks, are not necessarily known to both of the groups.

We construct three organizations of interest, where there are no pre-determined task assignments, and agents actively seek tasks according to their self and/or organizational interests. The three organizations to be compared are as follows:

- ORGA is self-synchronized organization, where decision makers have no collaboration. Agents identify and execute tasks purely based on their own interests and resource capabilities, i.e., each agent selects tasks for identification or execution, only if they can finish them solely. Furthermore, there is no information sharing between the two groups, therefore the agents cannot know the status and processing details of tasks identified by the other group.

- ORGB is an organization where the two groups collaborate both during the identification and execution phases. Here the agents coordinate their resources in processing the tasks to achieve the organizational overall goal.
- ORGC is an organization having resource collaboration within groups and inter-group information sharing. In addition to the intra-group resource collaboration as in ORGB, ORGC has one agent (A4) playing the role of information coordinator, maintaining synchronization of information between RepositoryA and RepositoryB. Therefore, the processing requirements and the status of the tasks identified by one group can be known to the other group.

The detailed parameters of mission and organization setting of the example system are as follows:

- Resources: There are 8 types of reusable and non transferrable resources; among them, 4 types can be used for task identification, and 6 types are for task execution. Therefore, some resources can be utilized both for task identification and execution.
- Mission tasks: The inter-task dependencies are encoded in the graph shown in Fig. 4, where there are 6 composite tasks, each has one identification sub-task and one execution sub-task. Mission tasks usually require longer processing time, more resources, and higher workload as compared to time-critical tasks. The processing time requirements of mission tasks for identification and execution phases lie in the range of (3, 5) and (8, 10) time units, respectively. Each mission task identification requires, on an average, two types of resources, and 10 units of resources in the total amount, while each execution sub-task requires, on an average, 3 types of resources and 30 units of resources in the total amount. The workload of each identification sub-task is on average 5 units per unit time, and execution task is about 10 units per unit time.
- Time-critical tasks: There is a total of 10 types of time-critical tasks. Similar to mission tasks, each type of time-critical task has one identification and one execution sub-task. These tasks randomly appear during the mission process with an average rate of once every 2 time units. The identification sub-task needs one resource type of 4 units on average. The execution sub-task needs, on an average, two types of resources, and 6 units in total amount. The processing times of identification and execution sub-tasks are distributed in the range of (1,3) and (5,8), respectively. The lifespan of time-critical tasks is uniformly distributed between (10, 20) time units. The workload of each identification sub-task is on an average 2 units per unit time, and the execution sub-task is about 7 units per unit time. The knowledge of each time-critical task's presence and identification requirements is randomly assigned to either GroupA, or GroupB, or both.
- Agents: Each agent possesses 4 types of resources, and 40 units in amount; The workload threshold for each agent is 20 units per time unit. When the agent is collaborating with another agent(s) to process a task, the workload imposed on a participating agent is proportional to the amount of resources the agent contributes.

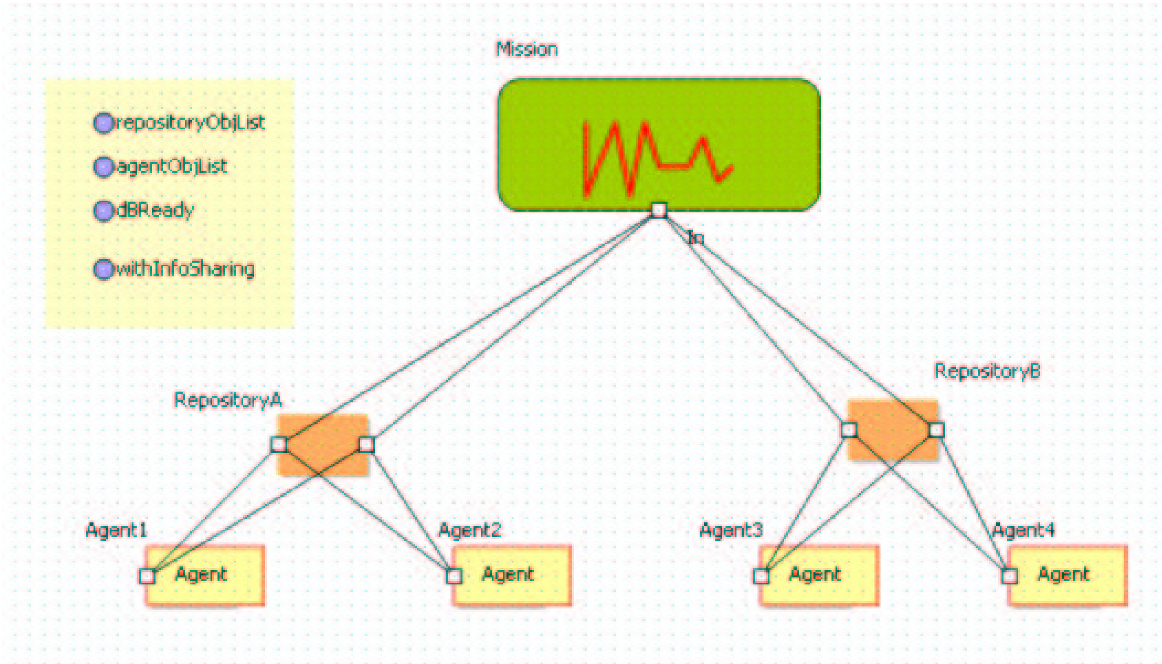

Fig. 3. Example Organization Structure

- The simulation stops whenever all the last mission task finishes or the maximum system time (200 time units) is reached.

The performance metrics for the example organizations being compared are listed in table I. The results demonstrate, as one can expect, that collaboration and information sharing facilitate higher organizational performance, which manifests itself as higher completion rate of mission tasks, the shorter mission completion time, evenly distributed workload among agents, the higher rate of tasks being identified and being executed; smaller number of task disappearing without being processed, and better resource utilization.

IV. Summary

In this paper, we proposed a modeling and simulation methodology for organizations involved in stochastic mission environments. In our model, organizations are constructed in terms of interacting components, namely, work, agents and the organizational structure, which depicts the assignment of work to agents, and communication and coordination among agents. The effectiveness of an organization reflects the congruence of these organizational components. Our generic model and agent-based simulation can facilitate the analysis of interplay of information collection (task identification) and decision making (task execution) processes, as well as the information flow behaviours in organizations in the face of stochastic mission environments. In these mission environments, task arrivals are stochastic, the characteristics of tasks are not known a priori, but maybe inferred to a certain degree by undertaking the information collection or task identification processes. Through the information collection processes, the organization collects the relevant attributes of tasks to estimate the resources necessary for their execution. This

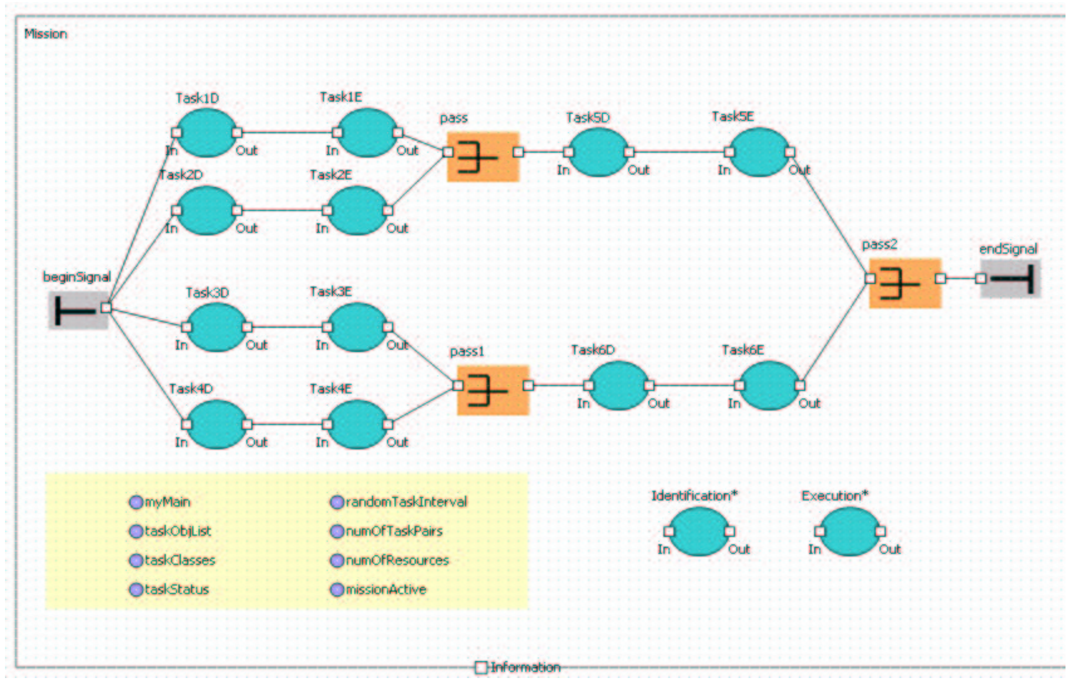

Fig. 4. Example Mission Structure

information is then used to allocate resources effectively for the execution of tasks. The organizational model is implemented using the $ANYLOGIC^{\circledR}$ simulation package, which embodies a discrete event simulator. We also investigated a number of coordinating organizational structures operating in a stochastic mission environment to illustrate the potential of our modeling and simulation approach.

In our future work, we propose to consider more realistic and full-range of task interrelationships, sophisticated agent behavior model, and the impact of agent behavior on the task identification and execution. We will also investigate modeling and simulation of agent coordination and communication behaviours, modeling of information integration and dissemination along organizational hierarchies, and errors in information propagation.

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TABLE I
PERFORMANCE METRICS OF EXPERIMENT SYSTEM

Performance Metrics		ORGA	ORGB	ORGC
Mission Finished?		No	Yes	Yes
Number of mission task finished		11	12	12
Mission Completion Time		N/A	111	**66**
Rate of time-critical tasks identified		49.5%	94.6%	88%
Rate of time-critical tasks executed		13.5%	83.8%	71.4%
Rate of time-critical tasks disappeared without processing		39.2%	7.4%	10%
Rate of tasks identified by collaboration		0%	36.9%	60%
Rate of tasks executed by collaboration		0%	54.9%	70.6%
Rate of tasks executed due to information sharing		0%	0%	12.4%
Average time units between task appearance to identification		1.37	4.02	2.9
Average time delay between task identification to execution		4.0	6.2	8.2
Average workload per unit time of each agent	A1	0.165	4.33	4.46
	A2	0.09	5.53	6.95
	A3	2.53	7.34	5.14
	A4	0.48	4.04	5.23