A SYSTEMATIC APPROACH TO OPTIMIZE ORGANIZATIONS OPERATING IN UNCERTAIN ENVIRONMENTS: DESIGN METHODOLOGY AND APPLICATIONS[*]

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Abstract

This paper presents a comprehensive methodology for solving diverse problems arising in performance optimization of organizations operating in uncertain environments. We introduce a technique to decompose a multi-dimensional organizational design problem into a series of coupled sub-problems whose iterative solution produces a near-optimal organizational structure, and decision processes. We illustrate our approach via an example to provide a step-by-step visualization of the modeling of complex and uncertain missions, and of synthesizing the concomitant organizations to optimize different sets of design objectives, while satisfying organizational constraints. Our methodology incorporates algorithms for optimizing the expected outcomes, collaborative organizational strategies, distributed resource utilization, mission processing schedule, and information management in an organization. The methodology serves as a valuable tool to address many practical problems arising in organizational design.

1   Introduction

> "A design is what the designer has when time and money run out"
> *James Poole*

1.1 Motivation

One of the most important assets of a successful organization is its design: the goals and strategies, access to information, the structuring of task solution processes, the underlying expertise and the assignment of people to positions; in short, the way an organization operates. In general, a proper organizational design is critical to superior organizational performance. For example, an inefficient management structure inhibits organization's ability to analyze the information and to react to unforeseen events in a timely manner, increasing the likelihood of organizational failures. Similarly, a poor allocation of responsibilities within an organization could result in overtaxing some individuals and adversely affecting their conditions (e.g., by causing confusion, stress, and/or fatigue), which, in turn, may affect individuals' task-processing capabilities and/or their capacity to interact with other team members. Therefore, when choosing a specific task-processing strategy, an organization must first assess its feasibility and weigh the associated benefits (e.g., of reaching the specific goals) versus costs (e.g., schedule delays, resources and energy expanded, coordination overheads, losses incurred, and so on). As accelerating changes in today's world set new requirements for modern organizations, from military establishments to commercial enterprises, technologies for designing organizations to be more effective are of great interest not only to researchers, but also to the society as a whole.

Over the years, research in team decision-making has demonstrated that an organization operates best when its structure and processes fit, or match, the corresponding mission environment. Contingency theorists argue that organizational effectiveness is influenced by the "degree of fit" between the requirements of the environment and the characteristics of the organization [Burton98]. This premise led to the application of systems engineering techniques to the process of designing human organizations to optimize the *predicted* human team performance (e.g., [Levchuk97], [Levchuk98], [Pete98]). The systems engineering approach to organizational design is as follows. First, a quantitative model describing the mission and the prospective organization is built. Next, different criteria are combined into an objective function, and an organizational design is generated to optimize this objective function.

In general, organizational design addresses the problems of synthesizing organizational *structures* and *processes* to improve its ability to influence its environment (via appropriate

actions). As with systems whose dynamics can be modeled by stochastic processes [Boutilier98], the current state of the environment and the courses of organization's actions jointly determine a probability distribution over the possible future states of the environment and of the organization. The organization "prefers" certain states (i.e., goal states) to others, and therefore attempts to determine and execute courses of action that are likely to induce the corresponding states ("desired effects"). In many cases, organization's objectives involve parts of the environment that cannot be controlled directly (i.e., indirect *effects* of organization's actions). In general, stochastic processes, independent of organization's actions, may have impact on the effects of organization's actions; thus, a level of uncertainty is associated with the effects of organization's actions.

Various transformations of the environment denote *functions* that can be assigned to individuals. Individuals perform *tasks* (activities) to fulfill functions, and *resources* must be allocated to enable the execution of tasks. When an organization performs a function, it applies a control at a particular state of the environment in order to move it towards a target state. In general, the extent of potential organization's control over the environment is limited, since various stochastic events may transform the environment in a random fashion. The actual transition when executing a function is guided by environmental and organizational uncertainties that determine the conditional probabilities of transition. For example, a superior technology may promote the ability of an organization to successfully perform a specific transformation of the environment.

To overcome the inherent human limitations (e.g., upper bounds on load tolerance and on the rate of processing information), the work must be distributed among individuals to complete the mission. Individuals with different *expertise* and *capabilities* assume different roles. While mission decomposition into tasks provides a basis for balancing the effort among teammates [Levchuk98], the input-output relationships that link tasks (e.g., when the output of one task is used as an input to another task) defines the "flows" within the organization and/or between the organization and its environment. The corresponding interactions among individuals define organizational *processes*.

The distributed nature of a mission processing requires that individuals *communicate* to share information, indicate intent, and synchronize their actions. A dynamic and uncertain nature of the teamwork imposes the need to dynamically manage both the team and the mission. An efficient team management mechanism is a prerequisite for ensuring the cooperation of individuals in their pursuit of organizational goals. The hierarchical management structure exploits specialization and division of teamwork to decompose control responsibilities and to assign them to positions linked together in a hierarchical pyramid. Various management and communication structures can be evaluated in terms of the following measures:

- *coordination efficiency* – e.g., coordination overhead, link contention, message latency, network connectivity, etc.;

- *task processing effectiveness* – e.g., resource redundancy, load balancing, etc.; and

- *structural flexibility* – e.g., the ability to reallocate the management and operational load without altering the team structure.

1.2 Organization of the Paper

This paper outlines a formal design methodology that integrates *four models* to address and characterize the organizational challenges from different perspectives. Each model describes a

generic design problem that addresses its own set of organizational challenges and aims to optimize its own set of criteria. As will be illustrated throughout this paper, the corresponding problems can be solved independently as well as iteratively to design various aspects of an organization. The corresponding problems are:

Problem 1. Choosing goals and actions to induce desired *effects* (Section 2)

Given an initial environment state, the problem is to find a set of actions (a *strategy*) together with their start times that will bring the environment to a specified destination (achieve a set of desired effects) before a deadline with the highest probability [Tu02]. We represent the joint dynamics of an organization and environment as a Dynamic Bayesian Network (DBN) identifying the cause-effect relationships, and use the genetic algorithms to search for a near-optimal strategy (with DBN serving as a fitness evaluator).

Problem 2. Optimize the *functional allocation* to achieve desired *goal states* (Section 3)

A *state* of the system is defined by a set of parameters, including probabilities of achieving desired goals, time, and resources available to an organization. For each system state, a set of functions that can be applied by an organization and the corresponding conditional probabilities of moving from one state to another while applying this function is determined using problem 1. The solution is obtained via Dynamic Programming (DP) recursion or graph search for a layered state graph [Meirina02]. We obtain the strategy that specifies the functions to be applied by an organization at any state to reach the end state with the highest probability.

Problem 3. Distributed dynamic *scheduling of event-driven tasks* (Section 4)

In this problem, the functions are decomposed into sets of tasks, and we present a methodology to dynamically schedule the tasks faced by the organization [Levchuk02a&b]. The need to execute a specific function, and as a result to process a set of tasks that comprise this function, is guided by the current state of the system (the state that system has moved to under environmental uncertainties).

Problem 4. *Mapping a task flow* onto the processing network (Section 5)

The input-output relationship and information flow dependencies among mission tasks are modeled by a directed acyclic communication graph. In this problem, we map the communication graph, or *task flow*, onto a network of organizational elements under workload capacity, memory capacity, and link bandwidth constraints [Levchuk02c]. The objective is to minimize the completion time of the mission, which is influenced by the task processing and communication delays. The issue of message contention in the agents' network is considered.

2 Effects-based Mission Planning

2.1 Example 1

A company designs, manufactures, and sells a set of products for a specific market. The ultimate goal of the company is to maximize its profit, which is a function of the company's own supply of products and of the number of orders the company receives from the customers. The company can affect its supply, characterized by the variety and quantities of products produced, and by the product quality and price, via various actions that include:

(a) improving the quality of existing products;

(b) changing the number of units manufactured;

(c) reducing the average unit cost; and

(d) developing new product(s).

The price of each product is a function of both the supply (consisting of the company's own supply and the supply from competitors) and the demand. The company cannot directly influence the demand, which is a function of the population demographics and of customers' preferences and priorities. The customers' preferences and priorities depend on several factors, including customers' income, tastes, lifestyles, and their familiarity with various products. The latter is characterized by customers' awareness of the features of various products, by the experience with some of these products, as well as satisfaction derived from the above experience. The company can affect the customers' familiarity with its products via marketing actions, such as advertising and promotional sales; but so can the company's competition. The company must choose a strategy (i.e., the company must decide which actions to apply and when) to maximize the expected profit.
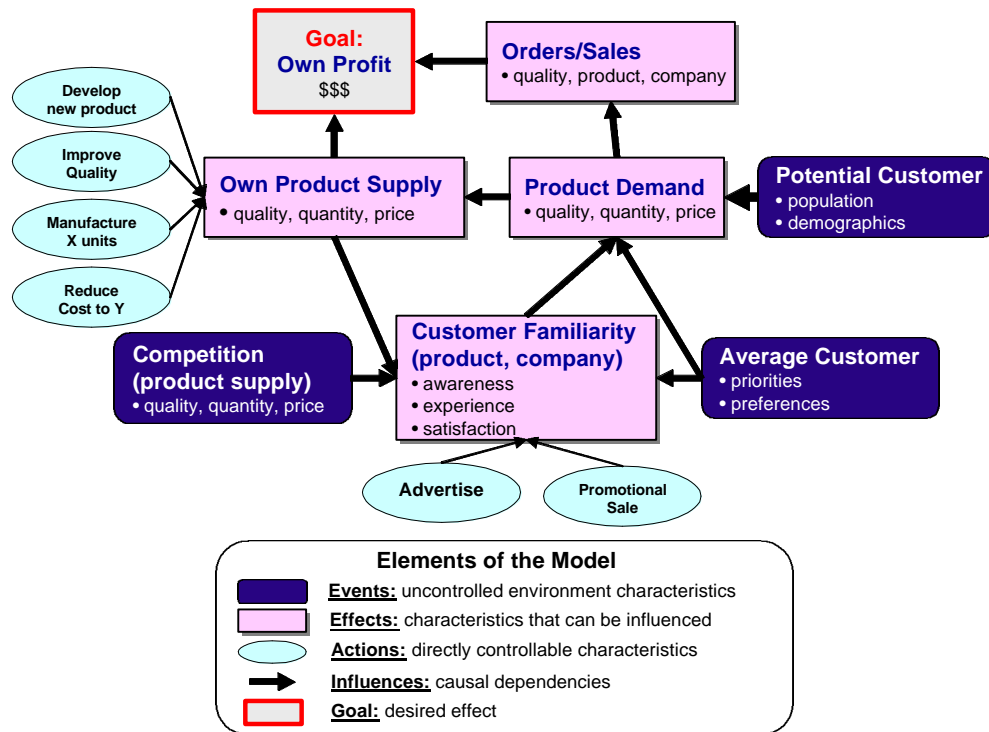
Figure 1. Environmental characteristics and their mutual influence

To visualize the interplay among the market characteristics that influence the company's profit, we define the company's environment of interest and specify the influence dependencies among its variables. First, we identify the company's environment of interest to include (see Fig. 1):

  (i)   variables directly controllable by the company[1], termed *actions*

  (ii) variables independent of the company's actions, termed independent *events*; and

  (iii) variables whose states can be influenced by the company's actions and/or by the independent events, termed *effects*.

Various numerical parameters characterizing an event (e.g., the trade-off coefficients between the product quality, price, and expected sales characterizing the demand; see Fig. 1) define the dynamic state of the event. We assume that events represent random processes whose expected

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[1] The variables representing environmental characteristics are called *directly controllable* by the organization if it can manipulate their dynamic states at will

values are known. Effects are modeled as random processes whose distribution is affected, to various degrees, by organization's actions, events, and the previous state of the environment. Some actions can be modeled as binary variables (e.g., develop a new product). In other cases, the company can manipulate the extent of the corresponding actions (e.g., the company can vary the number of units manufactured during different time periods), so that the action can be modeled as a continuous variable. One can define the dynamic state of each action to reflect whether the action is taken and to what extent (action's state being zero at a specific instant indicates that the corresponding action is not taken at that instant). The company may specify the desired states of specific effects, termed *goals*, (e.g., the desired profit), to define the company's objectives. We can depict the dependency relationships among the environmental characteristics as in Fig. 1. Some of the environmental characteristics may be unobservable (e.g., the abstract characteristic of the average customer; see Fig. 1). The dynamic observations of events and the knowledge about influence mechanisms (some of which may be hypothesized) can guide the company's selection of the appropriate action strategy to achieve the desired effects.

2.2 Influence model of the environment: actions, events, effects, and goals

In many cases, such as in example 1, an organization seeks to influence those aspects of the environment over which it has no direct control. That is, the organization's ultimate objectives can only be influenced, but not defined, by the outcomes of organization's actions [Tu02]. The ability of an organization to choose appropriate actions to induce the desired indirect effects depends on its ability to predict the potential influence from its actions on the dynamics of the environment. Given the dynamic nature of the world, with new opportunities and competitive threats arising in a seemingly random fashion, an organization often aims to create the specific effects at the right place and at the right time. However, environmental conditions also affect the feasibility of organization's actions, making some strategies more likely to succeed than others. To formalize the interaction between an organization and its environment, we define the *Influence Model* (IM) of the organizational environment[2]. The IM defines the parameters of a Dynamic Bayesian Network (DBN) that portrays the evolution of the environment [Tu02]. The IM and the corresponding parameters of DBN are summarized in Tables I and II.

A dynamically evolving effects-based mission at time $t_k, k \geq 0$ is modeled via a Dynamic Bayesian Network (DBN) – a directed graph $G(t_k) = (V^k, E, P^k)$. The model combines the knowledge about the organization and its environment at each time t_k. The set of nodes in the graph V^k (representing *environmental dynamics*) is decomposed into action, event, effect, and goal nodes: $V^k = V_u^k \cup V_n^k \cup V_e^k \cup V_g^k$. Without loss of generality we assume the graph structure to be time-invariant. Every node $v_i^k \in V^k$ is modeled as a random variable. For each node $v_i^k \in V^k$, we define a probability distribution $P^k(v_i^k) = \Pr\{v_i(t_k)\}$ at time t_k. The calculation of state probability is done recursively based on the following parent conditioning:

$$P_{k+1}(v_i) = \Pr\{v_i(t_{k+1})\} = \sum_{\Pi[v_i]} \Pr\{v_i \mid \Pi[v_i]\} \cdot \Pr\{\Pi[v_i](t_{k+1}) \setminus v_i(t_k)\} \cdot P_k\{v_i\}.$$

The cost of applying action i is equal to of c_i units. The cumulative cost of actions should not exceed a cost threshold $C_{\max}$.

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[2] An organizational environment is defined as a set of characteristics (e.g., objects and notions) with quantifiable features that jointly define the *state* of a characteristic.

TABLE I. AN INFLUENCE MODEL FOR EFFECTS-BASED MISSION PLANNING: ELEMENTS

Variables	Property	Description	Dynamics	State of Variable
Actions	directly controllable	$V_u \quad \{u_i, i \quad 1,..., N_u\}$	$u_i^k \quad u_i(t_k) \quad \{0,1\}$	=0 when no action is taken at time t_k =1 when action is executed at time t_k
Events	uncontrollable	$V_n \quad \{n_i, i \quad 1,..., N_n\}$	$n_m^k \quad n_m(t_k) \quad \{0,1\}$	=0 when event does not occur at time t_k =1 when event occurs at time t_k
Effects	influenced	$V_e \quad \{e_i, i \quad 1,..., N_e\}$	$e_j^k \quad e_j(t_k) \quad \{0,1\}$	=0 when effect is not achieved at time t_k =1 when effect is achieved at time t_k
Goals	desired effects	$V_g \quad \{g_i, i \quad 1,..., N_g\}$	$g_r^k \quad g_r(t_k) \quad \{0,1\}$	=0 when goal is not achieved at time t_k =1 when goal is achieved at time t_k

TABLE II. AN INFLUENCE MODEL FOR EFFECTS-BASED MISSION PLANNING: RELATIONSHIPS

Elements	Explanation	Description	Remark
Edges	arcs in the graph corresponding to probabilistic influences in Bayesian Network	$E \quad \{e_{i,j} \qquad v_i, v_j \quad \}$	arcs define causal relationships among nodes in the graph
Node Parents	set of nodes that directly influence node **v**	$(v) \quad \{z \quad V: \quad z, v \qquad E\}$	if a current state of the node depends on its previous state, then $v_i^{k\ 1} \quad (v_i^k)$
Probabilistic Influences	conditional probabilities	$\Pr\{v \mid \quad (v)\}$	probabilities of node state are conditioned on (influenced by) state of nodes' parents

2.3 Baseline Problem Formulation for Effects-based Mission Planning

Given the initial state of the environment, and assuming the knowledge about mechanisms of interactions between organizational and environmental dynamics, the baseline problem for effects-based mission planning is to find a set of dynamic actions (a *strategy*) that are likely to induce a set of desired environmental *effects* within a specified timeframe (e.g., on or before the prescribed deadlines) and with the highest joint probability of occurrence:

$$\hat{V}_u = \left\{ u_i(t_k), i = 1,..., N_u, k \geq 1 \right\}, u_i(t_k) \in \{0,1\}$$

The baseline problem is summarized in Table III. A solution to this problem can be found in [Tu2002]. Depending on the objective of the organization, the problem becomes:

• Maximize the likelihood of success – the problem becomes:

$$\max P(g_1 = 1,..., g_{N_g} = 1 \mid \hat{V}_u, V^0)$$

$$s.t. \sum_k \sum_{i=1}^{N_u} u_i(t_k) \cdot c_i \leq C_{\max}$$

• Minimize the time to achieve desired effects – the problem becomes:

$$\min K$$

$$s.t. \begin{cases} P(g_1 = 1,..., g_{N_g} = 1 \mid \hat{V}_u, V^0) \geq e \\ \sum_{k=1}^{K} \sum_{i=1}^{N_u} u_i(t_k) \cdot c_i \leq C_{\max} \end{cases} \quad (e \text{ - probability threshold}).$$

• Minimize the cost of a strategy – the problem becomes:

$$\min \sum_k \sum_{i=1}^{N_u} u_i(t_k) \cdot c_i$$

$$s.t. \quad P(g_1 = 1, \ldots, g_{N_g} = 1 \mid \hat{V}_u, V^0) \geq e$$

- Maximize the pay-off from the effects achieved – the problem becomes:

$$\max \sum_{i=1}^{N_g} R_i P(g_i = 1 \mid \hat{V}_u, V^0)$$

$$s.t. \sum_k \sum_{i=1}^{N_u} u_i(t_k) \cdot c_i \leq C_{\max} \quad,$$

where R_i is the reward for achieving goal g_i.

TABLE III. BASELINE PROBLEM FOR EFFECTS-BASED MISSION PLANNING

Given
• A set of environmental characteristics, and their initial conditions
• A set of potential events and their distribution
• A set of potential controllable actions
• Effects – part of the environment affected by events/actions (but those that are not goals) and their initial states
• Goals – desired effects and their initial states
• Mechanisms of interdependencies among environmental characteristics – conditional probabilities
• Cost of actions
• Pay-off from each goal
Find
• A dynamic strategy (i.e., a sequence of actions at the corresponding time instances)
Constraints[3]
• Budget threshold should not be exceeded
Objectives[4]
• Maximize the likelihood of success
• Minimize the time to achieve desired effects
• Minimize the cost of a strategy
• Maximize the pay-off from the effects achieved

3   Choosing Functions to Achieve Mission Goals

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[3] Depending on the problem at hand, other constraints (e.g., precedence constraints among actions) may be introduced.
[4] Any combination of these can be chosen as objectives.

3.1 Example 2

In order to increase profits, the company described in example 1 decides to reduce the average unit cost for a specific product. The company can employ a number of alternative strategies to achieve this goal:

a) reduce the cost of manufacturing process;

b) find alternative suppliers to reduce the cost of materials used to manufacture the product;

c) optimize the cost of transportation for both material and product shipments alike;

d) reduce company's inventory costs; and

e) reduce the cost of order processing and other logistics.

Each of the above strategies leads to a specific goal that contributes to the ultimate goal of reducing the average unit cost. Furthermore, each strategy can be decomposed into a number of sub-goals, with different functions[5] required to achieve the corresponding sub-goals (e.g., achieving freight consolidation with just-in-time versus pre-planned shipment balancing would reduce the cost of transportation; the cost of materials can be reduced either by using cheaper materials or by finding a cheaper supplier for the existing materials; see Fig. 2). For each function, the company estimates the function's likely duration and the concomitant probability of success. The company must choose which functions to perform in order to achieve its ultimate goal. The company's rationale for choosing its strategy is to maximize the overall probability of success while minimizing the cost expended. If the budget allows, the company can pursue several alternatives in parallel, thus increasing the likelihood of success. However, the company must carefully choose its strategy, as some of the potential sub-goals may be incompatible or conflicting (e.g., buying the cheaper materials from different suppliers may inadvertently increase the cost of transportation).

To visualize alternative ways (some of which may be combined) to reach the company's objectives, one can draw a "roadmap" to the mission goals as a directed graph whose nodes represent goals and sub-goals and whose arcs represent functions (Fig. 2). In the above roadmap (Fig. 2), one may use auxiliary 'AND' nodes to indicate when the same function or sub-goal can lead to achieving different goals (e.g., automation of on-line order processing may lead to both reducing the storage cost and reducing the logistics costs; see Fig. 2). Similarly, one can use auxiliary 'OR' nodes to illustrate that several functions represent alternatives for achieving the same goal (e.g., both redesigning the assembly process with existing equipment and upgrading the equipment could lead to reducing the cost of manufacturing; see Fig. 2). The roadmap connecting goals and functions provides a transition model that can be used to calculate the likelihood of success for alternative strategies of achieving the objectives.

3.2 Transition model for transforming the environment: functions and states

In many cases, such as in example 2, an organization must find an efficient strategy for its mission execution. The ability of an organization to choose the best strategy from several alternatives is critical to superior performance [Hocevar99]. Oftentimes, the ultimate organizational goals (specifying the desired states of the environment) may be achieved via different, alternative transformations of the environment, with each potential transformation requiring specific activities to be carried out and leading to different intermediate sub-goals. We term various desired transformations of the environment as *functions*. A *function* may imply

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[5] We define functions as controlled changes in the environment (contrasting with events that represent uncontrolled changes in the environment).

both *an intent to change the state of the environment* and *a concomitant activity carried out to facilitate the corresponding change*. Some functions can be assigned to different organizational elements for simultaneous execution, thus facilitating distributed mission processing. Individual goals and functions need to be *prioritized* consistently to optimize team collaboration.
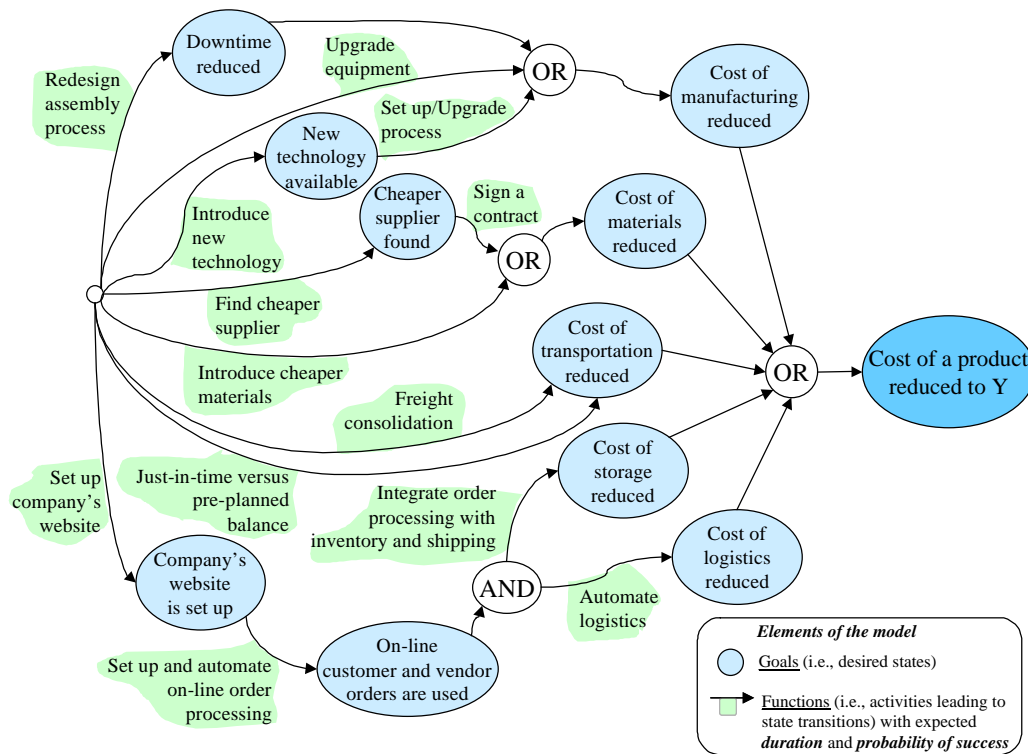

Figure 2. Functions-to-goals Roadmap

To formalize mission execution and dynamic strategy selection by an organization, we define the *Transition Model* (TM) for transforming organizational environment. The TM defines the parameters of a Dynamic Functions-to-Goals Roadmap (DFGR; Fig. 2) that portrays a strategy that is selected dynamically among alternative ways to achieve the organizational goals. In DFGR, different ways to achieve the same goal are represented by different paths leading to the goal (and possibly connecting intermediate sub-goals). Using this technique, one can visualize the *roadmap* to organization's goals (Fig. 2) by depicting the enabling interdependencies among various sub-goals and functions. Then, the problem of finding the optimal strategy to achieve organizational goals can be visualized as the problem of finding the "optimal" path or paths to organization's goals through the goal-function roadmap. DFGR uses such a roadmap to indicate the current state of the environment with respect to existing mission execution options and to indicate the dynamic status of functions being executed, thus providing an effective instrument to assist an organization in dynamically managing its goals and functions[6]. The TM is transformed into Markov Decision Problem [Meirina02]. The corresponding parameters are outlined in Table IV.

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[6] A *goal management* is the process of recognizing or inferring the goals of all individual team members; abandoning goals that have been achieved *or are no longer relevant*; identifying and resolving *conflicts between goals*; and *prioritizing goals* consistently for optimal team collaboration and for safe and effective operation. A *function management* is the process of identifying functions to achieve goals; defining/suggesting tasks to carry out functions; assigning actors to carry out functions and perform tasks; *assessing the status of each function* (whether or not it is being performed satisfactorily and on time); *prioritizing functions* based on goal priority and task/function status; and allocating resources to be used to perform tasks based on function priority.

TABLE IV. A MARKOV MODEL ELEMENTS FOR GOAL MANAGEMENT PROBLEM

Elements	Explanation	Description	Remark
Environment State	state of environmental characteristics	$i \in X \equiv \{1,...,N\}$	assume N states
Mission Goal (s)	desired state of environment	$i \equiv i^*$	
Time State	available time to execute a mission	$d \in [0, D_{\max}]$	time to execute a mission is equal to D_{max}
Resources State	available resources available to execute a mission	$r \in [0, R_{\max}]$	resources to execute a mission are equal to R_{max}
System State	expanded state, described by environment state, available time and resources	$\underline{s} \equiv [i,d,r] \in S$	
Functions	intended to transform the environment	$f \in F$	results from applying organizational resources
Functional Transformation	resulting system state after function application	$[i,r,d] \to [j,r - r(f), d - d(f)]$	
Transfer Function	conditional probability governing state transition	$\Pr(j\,|\,i,f)$	a transition from i to j is feasible if $r \geq r(f), d \geq d(f)$ and $\Pr(j\,|\,i,f) \geq 0$

More formally, the MDP approach can be formulated as follows. Let $S = [X, R, D]$ denote an *expanded state space* that includes the *resource state space* R and the *duration* dimension D (such that $D = [0, D_{\max}], D_{\max} \in I$ (integer), and $R = [0, R_{\max}], R_{\max} \in I$). The notation $X = \{1, 2, \Lambda, n\}$ denotes the *environment state space* whose elements represent different '*states of the environment characteristics*'. An organization has a set of control functions $F = \{f_m, m = 0,..., M\}$ that can be performed to move the system to a desired state. The function f_m is characterized as follows:

- f_m ($m = 1,..., M$) consists of applying a subset of actions from action set $A = \{a_k, k = 1,..., K\}$, therefore identifying the vector $\underline{y}_m = \{y_{m,k}, k = 1,..., K\}$ (where $y_{m,k} = 1$ if action a_k is used for function f_m, and $y_{m,k} = 0$ otherwise);

- f_m requires $r(f_m)$ resource units to complete and its duration is $d(f_m)$ units of time;

- when function f_m is applied to a system in expanded state $\underline{s} = (i, r, d)$, the system moves to state $\underline{s}_j = (j, r - r(f_m), d - d(f_m))$ with probability $P(\underline{s}_j\,|\,\underline{s}, f_m) = P(j\,|\,i, f_m)$ (where $\sum_{j=1}^{n} P(j\,|\,i, f_m) = 1$); and

- a "dummy" function f_0 is defined, such that

$$r(f_0) = 0, d(f_0) = 0, \quad y_{0,k} = 0, k = 1,..., K \text{ and } P(j\,|\,i, f_0) = \begin{cases} 1, & \text{if } j = i \\ 0, & \text{otherwise} \end{cases}$$

Accordingly, we construct a layered directed acyclic graph $G(S, E)$ representing a Markov chain of $N+1$ layers (number of layers is identified from the constraints of the problem). Nodes in

the graph correspond to expanded system states. $E = \{e_{\underline{s}_1,\underline{s}_2} =< \underline{s}_1,\underline{s}_2 >| \underline{s}_1,\underline{s}_2 \in S\}$ is the set of edges identifying the *probabilistically feasible* transitions among expanded system states.

The objective of the problem is to maximize the probability of reaching the goal state $P(i_N = i^*)$ subject to initial constraints $\overset{\rho}{s}_0 \in S$, $i_0, r_0 = R_{max}, d_0 = D_{max}$ and feasibility constraints. The solution to this problem can be found in [Meirina02].

3.3 Baseline Problem Formulation for Choosing Functions to Achieve Mission Goals

The baseline problem for choosing functions to achieve mission goals is to find a dynamic decision strategy (i.e., the optimal closed-loop decision policy) for choosing functions to maximize the probability of successfully achieving organizational goals (under resource and time constraints): $F^* = \{\langle f_i = f(\underline{s}_i)\rangle | \underline{s}_i \in S\}$.

Given the initial state of the environment and various functions (i.e., feasible transformations of the environment) that an organization can fulfill (e.g., by applying actions and resources), the corresponding problem is to find a sequence of functions (a *strategy*) that maximizes the probability of achieving a set of goals (representing the desired states of the environment) [Meirina02]. In our formulation of baseline problem for choosing functions to achieve mission goals, the conditional probabilities of transitioning between two given states as a result of applying a function are assumed known (they can be estimated from historical data or hypothesized). The baseline problem is summarized in table V.

TABLE V. A BASELINE GOAL MANAGEMENT PROBLEM

Given
• The initial system state
• Mission goal – end state
• Set of feasible functions and their characteristics
• State transition probabilities
Find
• Dynamic strategy (i.e., a sequence of designated actions and the corresponding time instances), corresponding to specific event dynamics, to achieve desired effects
Constraints
• Resource and time constraints may not be exceeded
Objectives
• Maximize the likelihood of success (i.e., of achieving mission goal)
• Minimize the time to achieve mission goal
• Minimize the cost of a strategy

4   Scheduling Distributed Event-Driven Mission Tasks

4.1 Example 3

Suppose that the company described in examples 1 and 2 was able to successfully develop the new technology and is now facing the need to upgrade its manufacturing process for the improved technology. Also, suppose that the changing market conditions force the company to periodically undertake various efforts directed at reducing the cost of its products, improving the quality of products, marketing the upgraded products, and so on. Specifically, suppose that the company decides to reduce the cost of its materials by changing the suppliers. The need to upgrade the manufacturing process and the decision to reduce the cost of materials represent two events that necessitate the completion of a series of tasks specific to each event. The corresponding tasks, as well as the concomitant task precedence constraints and the information transfer requirements between different tasks, are shown in the event-task graph in Fig. 3. Similarly to the two events depicted in Fig. 3, other expected events (e.g., improving the quality of products, marketing the upgraded products, and so on) also necessitate the completion of a series of tasks (the corresponding portion of the event-task graph is not shown). Different events may repeat themselves (e.g., the company may have to upgrade its products repeatedly over time), forcing the company to repeat the completion of the corresponding tasks. For each expected event, the company estimates its likely distribution of occurrence over time (e.g., the company may estimate the frequency and/or density of events). Each task necessitates the specific expertise and resource requirements, as well as the cognitive load imposed on a human agent performing this task. In addition, the company estimates the expected duration for each task and the expected duration of information transfer between tasks.
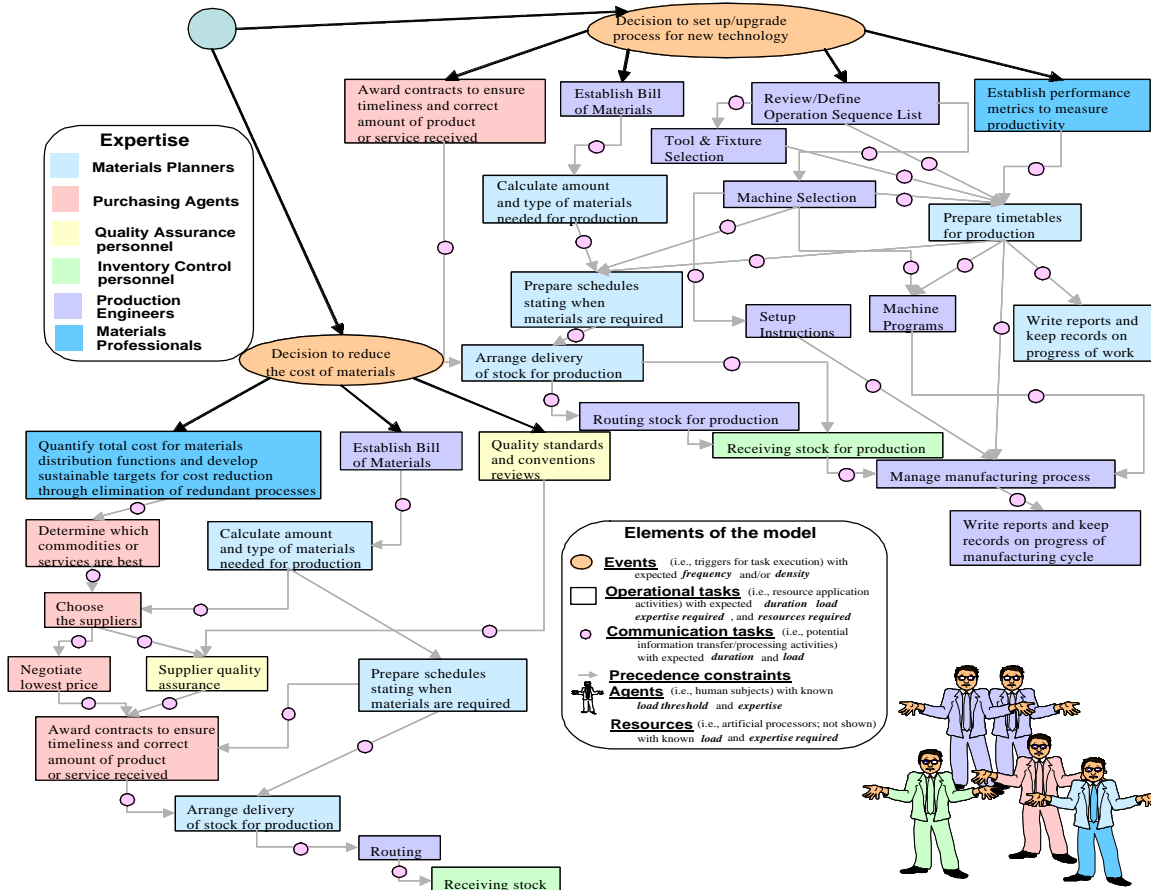

Figure 3. Distributed Event-Driven Tasks

We assume that the information transfer between tasks needs to occur only when the two corresponding tasks are assigned to different human agents (the agent processing the first of the two tasks needs to communicate the knowledge gained during the above processing to the agent assigned to the second task). For each human agent, the company estimates his cognitive load tolerance threshold and his expertise. Based on the make-up of expected events and the corresponding tasks and their requirements, the company must estimate the workforce required to support the prospective task work (i.e., the company must decide which experts and how many are needed). The company can rely on its personnel (on those whose expertise relates to the abovementioned tasks), including (see Fig. 3): (i) material planners and material management professionals; (ii) purchasing agents; (iii) inventory control personnel; and (iv) production engineers. The company may choose to hire additional personnel to support its task work requirements (e.g., to support all the task expertise requirements, it will need to hire quality assurance personnel; alternatively, the company may choose to outsource some of its tasks rather than hiring the new personnel). The company must also decide which resources to employ to satisfy the task requirements. Finally, the company will have to dynamically schedule all its tasks to be processed by the human agents, while using the allocated resources. The company's objectives may include minimizing the overall completion time, optimizing the utilization of resources and of the workforce, and minimizing the overall cost incurred when completing different tasks.

To visualize the mission task requirements, we use a colored directed two-layered event-task graph (Fig. 3), whose nodes denote events (the upper layer) and tasks (the lower layer) and whose arcs denote event-task requirements (inter-layer connections) and inter-task information transfer requirements and task precedence requirements (inner connections of the lower graph layer). We can also use the color-coding to indicate the expertise requirements per task and to show the expertise of human agents available (Fig. 3). Similarly, one can also show the resources, the corresponding expertise requirements, and the resource-to-task feasible allocation map (for the sake of brevity, the resource aspect of the company is not shown in Fig. 3). The above formalism connecting the events, tasks, resources, and human agents constitutes the impact model of the distributed mission and organizational constraints (the model highlights the impact from events in terms of tasks needed to be performed and the impact on the human agents from processing the tasks and from operating the resources).

4.2 Transition model for event-driven mission: events, tasks, agents, resources

The following elements of organization and environment and their characteristics are modeled:

Operational tasks – parts of the mission to be executed by an organization. Successful task execution requires the application of appropriate resources and expertise, and induce cognitive load onto the organization. For operational tasks, the following attributes are modeled: *expected duration*, *expertise requirements*, *resource requirements/constraints*, and *cognitive load*.

Communication tasks – tasks in the mission that require transfer of information among organizational elements. For communication tasks, the following attributes are modeled: *amount of information*, *origin-destination* pairs (of elements in the organization), and *cognitive load*.

Events – occurrences that change the state of the environment and induce the introduction of operational and/or communication tasks to be executed by an organization. For events, *expected frequency* of occurrence is modeled. The structure of an event is defined by specifying the *task prerequisites* and *inter-task information flow*.

Resources – elements/assets of organization that can be used to physically execute the operational tasks. For each resource, *task capabilities*, *expertise requirements/constraints*, and *cognitive operation load* are specified.

Agents – human decision-making elements of an organization, with *expertise*, *workload threshold* and *communication capacity* constraints.

The problem formulation and its solution can be found in [Levchuk02a&b].

4.3 Baseline problem formulation for scheduling event-driven mission tasks

A baseline problem formulation for scheduling event-driven mission tasks is summarized in Table VI.

TABLE VI. A BASELINE EVENT-DRIVEN MISSION TASK SCHEDULING PROBLEM

Given
• Tasks and their characteristics (expected duration, expertise requirements, cognitive load)
• Events and their characteristics (occurrence, event-to-task mapping, task precedence and information transfer requirements inside event, task deadlines, etc.)
• Resources and their expertise requirements and operation cognitive load, resource capabilities (resource-task feasible allocation); resource utilization cost per unit time
• Agents and their characteristics (cognitive load tolerance threshold, expertise, cost, etc.)
• Budget constraints
• Pay-off from tasks
Find
• Dynamic strategy (i.e., the allocation of tasks-to-resources-to-agents and the corresponding time instances for initiating task processing), corresponding to the specific distribution of events over time, to complete the mission
Constraints[7]
• Budget constraints may not be exceeded
• Resources can be involved in processing only one task at a time
• Resource can be operated only by a single agent who possesses required expertise
• Tasks can be processed only by agents who possess the required expertise
• Agent's cognitive load tolerance threshold may not be exceeded
Objectives[8]
• Maximize the likelihood of success (i.e., of completing all the tasks by the time required)
• Minimize the time to complete tasks
• Maximize resource utilization
• Minimize the cost of a strategy
• Minimize excessive communication
• Maximize the pay-off from tasks completed

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[7] Depending on the problem at hand, other constraints (e.g., precedence constraints among actions) may be introduced.
[8] Any combination of these can be chosen as objectives.

5   Mapping Inter-Task Information/Commodity Flow onto Agent Network

5.1 Example 4

For the company described in examples 1, 2, and 3, the interdependences among its mission tasks (such as the *information flows* and/or the *commodity flows*[9]) necessitate the input-output exchange among various organizational and outside elements (e.g., agents, departments, production plants, warehouses, suppliers, retailers, etc.). Some of the examples of input-output flow are:

a) research of the customers' preferences must find its way into the design of the company's products;

b) technology and design aspects will render the specific manufacturing and assembly process descriptions to guide the transformation of the materials into products;

c) materials must be purchased and delivered to the production sites;

d) ready-to-sell products must be packaged and delivered to the warehouses and retailers;

e) customers' orders must be processed and the flow of shipments must be distributed accordingly;

f) financial flows must be set up properly; etc.

In short, a multitude of interrelated flows ties up various elements of the company and the environment, from market research to design to manufacturing, and from supply of materials to assembly to warehousing to retailers and/or to customers. The existing infrastructures within and outside the company's organizational structure (e.g., management and logistics, departmentalization, information transfer, communication, and transportation structure) specify the means for, the constraints on, and the cost of carrying out the input-output flows. Specifically, suppose that the company produces two different products using three different types of materials (Fig. 4). The company can buy the materials from several suppliers at various locations and at various pricing options. The materials are to be delivered to two different assembly plants for manufacturing. The company must decide which of the two sites would be involved in the assembly of which products (or of which product parts). After the products are assembled, they are to be shipped, directly or via the warehouses, to both the retailers and the on-line customers according to the orders received. The company has several options when managing flows that tie up different processes and organizational elements:

- augment company's processes to include new flows or to remove some of the flows;

- change the connectivity of its flows to include or remove organizational elements (i.e., agents, which work as flow processors) and/or flow channels;

- specify different flow transition medium and vary its operating rules;

- vary the allocation of processing flow tasks to agents (organizational elements), thus changing the ensuing input-output flow structure; and

- schedule flows across the corresponding channels in a different manner, affecting the task synchronization and the flow transition timeliness and cost.

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[9] E.g., the flow in a production cycle that transforms the raw materials into ready-to-sell products.

For example, the company may decide to begin the production of a third product, and must readjust its flows accordingly. The company's objectives may include minimizing the flow cost, minimizing the average flow transition time, optimizing the flow cycles, optimizing the connectivity among organizational elements, optimizing the supply (e.g., just-in-time and/or just-as-much-as-needed), balancing the load on the flow channels, and synchronizing the flows (e.g., according to a pre-specified production schedule).

To visualize the interplay of various information and commodity flows and the concomitant problems for optimizing the flows, we introduce the flow model of organizational environment (Fig. 4). First, we tie the input requirements with the output capabilities for various tasks to form the "building blocks" for constructing flows. Second, we introduce a specific "baseline" flow transition and processing scheme as a directed graph whose arcs denote the corresponding flows and whose nodes correspond to flow processing tasks (Fig. 4). We also associate the flow processing capabilities with various organizational elements (agents). The organizational agents connected via communication channels form an agent network. With every channel, we associate the flow throughput capacity tying the flow volume with the transition time and cost. For example, the distances and the transportation means among the production plants, warehouses, and shipping centers set physical constraints for transporting materials and goods. On the other hand, the logistics standards (e.g., the customer order processing tied to shipments scheduling), the management and process control routine, the accounting standards and procedures, and the information technology available also present various constraints on the information flows. These and other similar constraints can be modeled as capacity constraints for the corresponding flow channels.
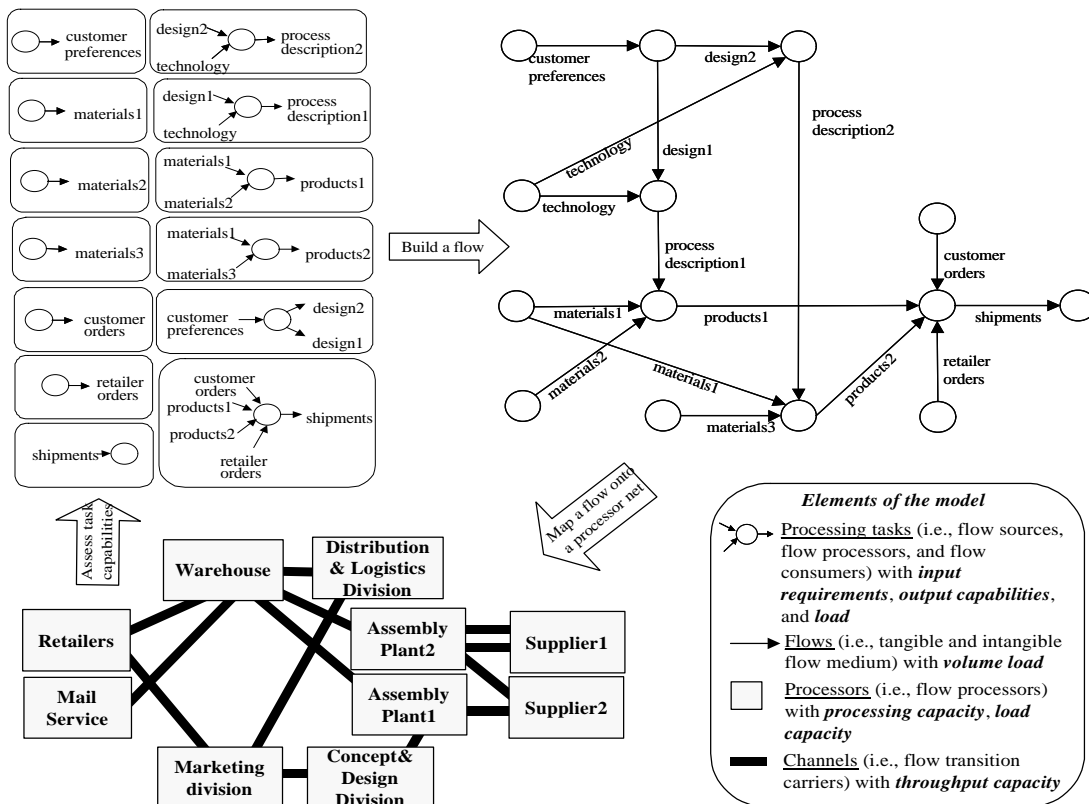

Figure 4. Building a Mission Input-Output Flow Structure

5.2 Flow model: information tasks, organizational agents

To identify the flow structure, the organization needs first to define *information tasks* as origin-destination nodes for information flow. Information tasks are modeled via directed acyclic *information graph* $G_t = (V_t, E_t)$, where $V_t = \{T_i, i = 1,..., N\}$ is the set of task nodes, $N = |V_t|$ is the number of nodes, $E_t = \{e_{i,j}^t = <T_i, T_j>\}$ is the set of directed edges, and $e_t = |E_t|$ is the number of edges. Edges in the graph correspond to communication messages and precedence constraints among tasks. Amount of information (weight of communication) transmitted from task T_i to T_j (incurred along the edge $e_{i,j}^t = <T_i, T_j>$) is denoted by $f_{i,j}$, which becomes zero if both tasks are allocated to the same agent. For each task T_i, a processing load (or *workload*) w_i and memory load m_i are defined.

The agents in organization are modeled via another dependency graph. The agent structure is defined by an undirected graph $G_a = (V_a, E_a)$, where $V_a = \{A_r, r = 1,..., K\}$ is the set of agent nodes and $K = |V_a|$ is the number of nodes, and $E_a = \{e_{r,u}^a = <A_r, A_u>\}$ is the set of undirected communication links among agents with transfer rate $c_{r,u}$, and $e_a = |E_a|$ is the number of links. For each agent A_r, a processing (or *workload*) capacity W_r and a memory capacity M_r are defined, and the time to process task T_i is $p_{r,i}$ ($p_{r,i} = \infty$ if the agent cannot process this task; we assume that $p_{r,i} = \infty$ if $W_r < w_i$).

TABLE VII. INFORMATION TASKS AND AGENTS DATA FOR FLOW MAPPING PROBLEM

Mission Description

Elements	Explanation	Description
Information Task	part of the mission to be executed; incurs info flow in organization	T_i V_t
Communication Graph	directed acyclic graph of tasks with precedence constraints	G_t (V_t, E_t)
Flow/Precedence Arc	identifying flow weight $f_{i,j}$ and origin/destination of flow	$e_{i,j}^t$ T_i, T_j E_t
Task Workload	processing load incurred on agent executing a task	w_i
Memory Load	cognitive load incurred on agent executing a task	m_i

Organization Description

Elements	Explanation	Description
Agent	human decision-making element of organization	A_r V_a
Agent Network	non-directed graph of agents representing communication structure	G_a (V_a, E_a)
Communication Link	identifying possible communication path and its capacity Remark: rate of information transfer between agents on the link is specified: $c_{r,u}$	$e_{r,u}^a$ A_r, A_u E_a
Agent Processing Capability	time required to process a task T_i	$p_{r,i}$
Agent Workload Capacity	identifying the aggregated load of tasks that agent A_r can process in parallel	W_r
Agent Memory Capacity	identifying the aggregated load of task information that agent A_r can store simultaneously without information loss	M_r

The execution model works as follows (for a similar macro-dataflow model, see [Sarkar89], [Wu88]). The data flow triggers the execution of tasks. A task receives all data from its predecessors in parallel. It then executes without interruption (non-preemptively) and immediately after completion it sends the data to all successors in parallel. In this model, task execution and agent communication are done in parallel subject to constraints on workload and memory capacities, and communication contention.

The processes of an organization assigned to execute a mission consisting of information tasks can be conceptualized as follows:

❑ Task execution (processing) by organizational agents

❑ Agent communication – routing task information flow among agents

❑ Storing of tasks in the agent's memory

Solution to task flow mapping problem can be found in [Levchuk02c]. Task and agent attributes are outlined in Table VII.

5.3 Baseline problem formulation for mapping flows onto agent network problem

Task Execution

To complete a mission, every task is allocated to a single agent capable of processing this task. When a task T_i is processed by an agent A_r, the latter's workload is increased by w_i units. Agents can generally process more than one task at a time, but the dynamic workload (total load of simultaneously processed tasks) of any agent A_r must not exceed agent's workload capacity W_r. A task can begin to be processed by an agent when all the predecessors of a task have been completed and all the information flow from them was communicated to this agent.

Agent Communication

If tasks T_i and T_j are assigned to different agents, information $f_{i,j}$ must be communicated between these agents in the organization (communication is zero if these tasks are assigned to the same agent). The agents can communicate only one message at a time. The time required to communicate $f_{i,j}$ units of information from agent A_r to A_u along the link $e^a_{r,u}$ is equal to $\dfrac{f_{i,j}}{c_{r,u}}$ if $c_{r,u} \neq 0$. We could generalize the problem formulation by making this time dependent on tasks and on the link between communicating agents.

We assume that only connected agents communicate, and if $c_{r,u} = 0$, then communication between these agents cannot occur. Another approach is to allow such communication to occur through the shortest path between these agents in the network, assuming that the agent network is fully connected. In this case, the most efficient routing of information should be performed dynamically to account for communication link contention.

Task Storage

The storage of task T_i (in the agent's memory) is required if:

a) task T_i and its successor task T_j (the task that requires information from T_i) are assigned to the same agent A_r; in this case, the dynamic memory load of agent A_r is increased by m_i units from the finish time of T_i until the start time of T_j;

b) task T_i is assigned to agent A_r, but its successor task T_j is assigned to agent A_u ($u \neq r$); in this case, the dynamic memory load of agent A_r is increased by m_i units from the finish time of T_i until the time communication of information $f_{i,j}$ is initiated from agent A_r to A_u, and a dynamic memory load of agent A_u is increased by m_i units from the time information $f_{i,j}$ is received from agent A_r until the start time of task T_j.

The dynamic memory load of any agent A_r must not exceed its memory capacity M_r.

One of the objectives is to find a mapping of task structure onto agents' network and the corresponding task schedule that minimize the mission completion time (*makespan*) – the completion time of the last task. This problem can be viewed as consisting of three parts:

1. Allocation of tasks to agents.

2. Sequencing of task execution for each agent.

3. Sequencing of communication (due to task information flow) in agents' network.

Baseline problem formulation is given in Table VIII.

TABLE VIII. A BASELINE GOAL MANAGEMENT PROBLEM

Given
• Mission: tasks, task flows structure and constraints, task processing load, etc.
• Organization: agents and their capabilities, agent network topology and bandwidth, agent-to-task processing times (capabilities), agent operating cost, channel operating cost, etc.
• Budget
• Pay-off from flow consumption tasks
Find
• Input-output flow process design (i.e., a group of inter-dependent tasks with flow characteristics specified for the inter-task input-output relationships), corresponding to the flow consumption requirements and source constraints and to various flow processing alternatives, to complete the mission
• Agent-to-task assignment
• Information routing in agent network
Constraints[10]
• Budget constraints may not be exceeded
• Channel's capacity constraints may not be exceeded
• Agent's capacity constraints (workload and memory load) may not be exceeded
Objectives[11]

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[10] Depending on the problem at hand, other constraints (e.g., precedence constraints among actions) may be introduced.
[11] Any combination of these can be chosen as objectives.

- Minimize the total schedule of information graph (accounting for flow delays)
- Balance task load among agents
- Minimize flow contention, maximize channel utilization, minimize task latency
- Maximize the pay-off from flow consumption tasks completed

6 Summary and Future Research

The potential of applying systems engineering approach to designing organizations is enormous, which was clearly shown by experiments [Entin99], [Hocevar99]. This approach to designing man-machine systems allows for replacement of cumbersome centralized control with decentralized control and autonomy. Strict mathematical problem formulations provide the foundation for exploring ways to solve design problems efficiently and with the required degree of optimality to make best use of available time and computational resources. The latter is especially important for designing dynamic algorithms that help humans to adapt.

In this paper, we presented guidelines for model-driven synthesis of optimized organizations for a specific mission. The primary contributions of this paper include a formal method for representing missions and human-machine organizations. We showed how to decompose the problem of organizational design into a set of well-defined optimization problems. The iterative solution provides an efficient method to overcome the complexity of organizational design problem. The analytic methodology illustrated in this paper forms the basis for current research in organizational design and adaptation.

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