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# ANALYSIS OF PREPROCESSORS AND DECISION AIDS IN ORGANIZATIONS*

by

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## ABSTRACT

The use of preprocessors and decision aids in command, control and communication ($C^3$) systems is meant to reduce the workload of individual decisionmakers and improve the quality of an organization's decisionmaking. An information theoretic framework is used to model the decision aids. Thus, it becomes possible to evaluate quantitatively the effect a decision aid has on the workload of a decisionmaker and to derive necessary conditions that preprocessors (a generic form of decision aids) must satisfy in order that they reduce the human's workload.

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Abstract: The use of preprocessors and decision aids in command, control and communication ($C^3$) systems is meant to reduce the workload of individual decisionmakers and improve the quality of an organization's decisionmaking. An information theoretic framework is used to model the decision aids. Thus, it becomes possible to evaluate quantitatively the effect a decision aid has on the workload of a decisionmaker and to derive necessary conditions that preprocessors (a generic form of decision aids) must satisfy in order that they reduce the human's workload.

Keywords: Decision Aids, Organization Theory

## INTRODUCTION

The objective of the research presented in this paper is twofold: (a) to extend a mathematical theory of organizations to include decision aids and (b) to provide an interpretation of some recent experimental results on multiple tasking of decisionmakers. The unifying concept is that of a preprocessor - a processor located between the data source (or stimulus) and the situation assessment stage of a decisionmaker. A simple decision aid can be modeled by an external preprocessor while for interpreting the experimental results an internal preprocessor is introduced.

One function of decision aids is to reduce a decisionmaker's workload. One way of doing that is by pre-processing the incoming data. Another mechanism is to reduce the input rate by filtering out irrelevant data. This saves processing resources and increases the time available to process individual inputs. The decisionmaker need attend only to the significant data and therefore, the system performance is enhanced.

The model of the human decisionmaker used in this paper is the descriptive one presented in Boettcher and Levis (1982, 1984) and Levis and Boettcher (1983). The model of the preprocessor is linked to the decisionmaker model so that its ability to reduce the processing workload of the decisionmaker can be analyzed.

The basic information theoretic model of the decisionmaker is a two-stage process with limited processing capacity; it is illustrated in Fig. 1. The decisionmaker receives an input symbol x from his environment. If the input symbols are generated every $\tau$ seconds on the average, then $\tau$, the mean symbol interarrival time, is a description of the tempo of operations. The situation assessment (SA) stage consists of a finite number of well-defined deterministic or stochastic algorithms that the decisionmaker can choose from to process the measurement x and obtain the assessed situation z. The internal decision u in this stage is the choice of algorithm $f_i$ to process x. Therefore, each algorithm is considered to be active or inactive, depending on the internal decision strategy p(u). In the response selection (RS) stage, which is similar to the situation assessment stage, one of the algorithms $h_j$ is chosen according to the response selection strategy $p(v|z)$ to process the situation assessment z into an appropriate response y. Since no learning takes place during the performance of a sequence of tasks, the successive values taken by the variables of the model are uncorrelated, i.e., the model is memoryless. Hence, all information theoretic expressions in this paper are on a per symbol basis.

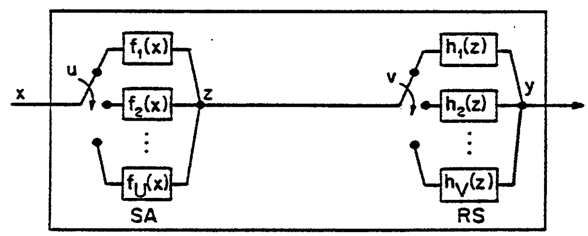


Figure 1. Basic Model of Decisionmaking Process

The model of the decisionmaking process shown in Fig. 1 may be viewed as a system S consisting of two subsystems, $S^{SA}$ and $S^{RS}$, that correspond to each one of the two stages. The input to this system S is x and the output is y. Furthermore, let each algorithm $f_i$ contain $\alpha_i$ variables denoted by

$$W^i = \{w_1^i, w_2^i, \ldots, w_{\alpha_i}^i\} \qquad i = 1,2,\ldots,U \qquad (1)$$

and let each algorithm $h_j$ contain $\alpha_j'$ variables denoted by

$$W^{U+j} = \{w_1^{U+j}, w_2^{U+j}, \ldots, w_{\alpha_j}^{U+j}\} \quad j = 1,2,\ldots,V \quad (2)$$

It is assumed that the algorithms have no variables in common:

$$W^i \cap W^j = \phi \quad \text{for } i \neq j \quad , \quad i,j = 1,2,\ldots,U+V \qquad (3)$$

The subsystem $S^{SA}$ is described by a set of variables

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$$S^{SA} = \{u,\ W^1,\ldots,W^U,z\} \quad (4)$$

and subsystem $S^{RS}$ by

$$S^{RS} = \{v,\ W^{U+1},\ldots,W^{U+V},y\} \quad (5)$$

The four quantities stated in the Partition Law of Information (Conant, 1976) for this system S can be evaluated with the following results.

Throughput:

$$G_t = T(x:y) = H(y) - H_x(y) \quad (6)$$

Blockage:

$$G_b = T_y(x:u,\ W^1,\ldots,W^{U+V},z,v) = H(x) - G_t \quad (7)$$

In this case, inputs not received or rejected by the system are not taken into account.

Noise:

$$G_n = H_x(S^{SA},\ S^{RS}) = H(u) + H_z(v) \quad (8)$$

Coordination:

$$G_c = T(u:w_1^1:\ldots:w_{\alpha_V'}^{U+V}:z:v:y) = G_c^{SA} + G_c^{RS} + T(S^{SA}:S^{RS}) \quad (9)$$

where

$$G_c^{SA} = \sum_{i=1}^{U} [p_i g_c^i\ (p(x)) + \alpha_i H(p_i)] + H(z) \quad (10)$$

$$G_c^{RS} = \sum_{j=1}^{V} [p_j g_c^{U+j}(p(z|v=j)) + \alpha_j' H(p_j)] + H(y) \quad (11)$$

$$T(S^{SA} : S^{RS}) = H(z) \quad (12)$$

The quantity H(x) denotes the entropy of the random variable x and $H_x(y)$ is the conditional entropy of y when x is given. The expression for $G_n$ shows that it depends on both internal strategies p(u) and p(v|z). In the subsystem coordination expressions $G^{SA}$ and $G^{RS}$, $p_i$ and $p_j$ are, respectively the probabilities that algorithms $f_i$ and $h_j$ have been selected, i.e., $p_i=p(u=i)$ and $p_j=p(v=j)$. The quantities $g_c^k$ represent the internal coordination of the corresponding algorithms and depend on the probability distributions of their respective inputs. The quantity H is the entropy of a Bernoulli random variable with parameter p:

$$H(p) = -\ p \log p - (1-p) \log (1-p) \quad (13)$$

Eq. (9) states that the total coordination in the system S can be expressed as the sum of the internal coordination within each subsystem given by Eqs. (10) and (11) and the coordination due to the interaction between the two subsystems given by Eq. (12).

The subsystem coordination consists of terms reflecting the presence of switching due to the internal decision strategies p(u) or p(v|z). If there is no switching, i.e., if, for example p(u=i)=1 for some i, then H will be identically zero and Eq. (10) will reduce to:

$$G^{SA} = g_c^i(p(x)) + H(z) \quad (14)$$

Finally, the total information processing activity of the system G is given by

$$G = G_t + G_b + G_n + G_c; \quad (15)$$

it can serve as a measure of the workload of the decisionmaker is carrying out this task. (Boettcher and Levis, 1982)

The paper has been organized as follows. In the next section, the basic model of preprocessors and decision aids is introduced. The preprocessor model is connected to the decisionmaker model for system evaluation. A numerical example is provided to illustrate the utility of a preprocessor in a decisionmaking system. Also, guidelines for the role of preprocessors in decisionmaking systems are developed. In the final section the question of how a preprocessor can facilitate dual-task processing by a decisionmaker is investigated by formulating two versions of a dual-task problem. and analyzing one of them.

## THE PREPROCESSOR MODEL

A preprocessor (PP) is located between a source and a decisionmaker (DM). In the simplest case considered here the PP operates on the decisionmaker's input variable only; hence, the PP consists of a single algorithm for preliminary processing of the input. It yields a SA decision strategy, p(u|x), and sometimes a modified input x' to the DM. Consequently, if the function of a PP is specified, i.e., the algorithm and the interconnections of the internal variables, the activity within the PP is computable, just like for the other algorithms within the SA and RS stages of the DM model.

A simple example of a PP illustrates how the various activity terms can be computed for a specified algorithm with well-defined internal variables. The function of the preprocessor in this example is to reduce the workload of the decisionmaker by processing some of the data before they are received by the DM. In order to evaluate the utility of the PP, two different decisionmaking systems, shown in Figs. 2 and 3, are considered.

The first one represents an unaided DM while the second one represents a DM with a preprocessor. The DMs in both systems is identical structures and algorithms. The PP in the second system is an algorithm that performs the same function as the SA stage of the first DM system. Since the PP is just an algorithm without any decisionmaking capability, the SA stage of the first DM system has to employ a pure strategy, i.e., the same algorithm is always selected to process the arriving inputs. Under such conditions, the decisionmaking process in both systems are identical. In order to allow the two systems to do the same task with the same performance, so that the activity or workload can be compared properly, the algorithms within the processes are assumed to be deterministic and their output distributions p(y) identical. The latter result will be ensured, if the RS stage in the DM of both systems has the same input distribution p(z) and decision strategy p(v|z). Since the second system has executed the SA job within its preprocessor, its SA stage simply transmits its input to an identity algorithm so that the distribution $p(z)$ within both systems will be identical.

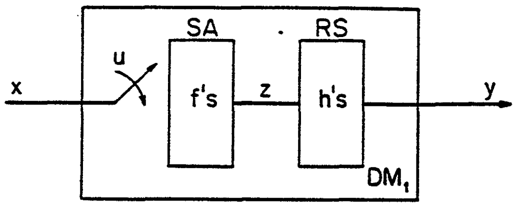


Figure 2. Basic DM System

With such a processing setup, the two systems carry out the same task with the same performance. To demonstrate the utility of the PP in the second system, the total activity within each system has to be evaluated.

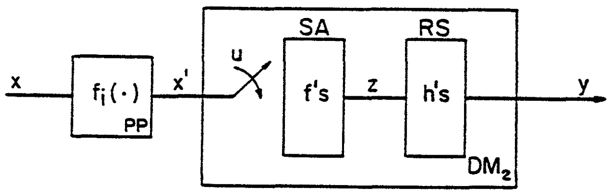


Figure 3. Aided DM System

Let:

$$G_{DM_1} = \text{Activity within First System} \quad (16a)$$

$$G_{DM_2} + G_{PP} = \text{Activity within Second System} \quad (16b)$$

where $G_i$ is the total activity with subsystem i.

The expression for the total activity of a decisionmaker is given by:

$$G_{DM} = H(x)+H(u) + \sum_{i=1}^{U} p_i g_c^i + \sum_{i=1}^{U} \alpha_i H(p_i) + H(z) + H_z(v)$$

$$+ \sum_{j=1}^{V} p_j g_c^{U+j}(p(z|v=j)) + \sum_{j=1}^{V} \alpha_j' H(p_j) + H(y) + H(z) \quad (17)$$

Since the response selection process, input distribution $p(z)$ and decision strategy $p(v|z)$ of the RS stage in both systems are assumed identical, the activity within the RS stage of the two systems is the same, denoted by $G_{RS}$.

$$G_{RS} = H_z(v) + \sum_{j=1}^{V} p_j \, g^{U+j}(p(z|v=j)) + \sum_{j=1}^{V} \alpha_j' H(p_j)$$

$$+ H(y) + H(z) \quad (18)$$

Assume that the pure strategy in the SA stage of the first system is such that the $i^{th}$ algorithm is always selected (i.e., $p(u=i)=1$) whereas in the second system the first algorithm, which is an identity algorithm, is always selected. Then the activity of each decisionmaker in the two systems is obtained from the expressions in Eqs. (17) and (18)

$$G_{DM_1} = H(x) + g_c^i + H(z) + G_{RS} \quad (19a)$$

$$G_{DM_2} = H(x') + g_c^1 + H(z) + G_{RS} \quad (19b)$$

The preprocessor in the second system consists of a single algorithm without any decisionmaking capability. The algorithm in this case is identical to the $i^{th}$ algorithm of the SA stage, hence the activity within the PP is simply

$$G_{PP} = H(x) + g_c^i \quad (20)$$

The function of the identity algorithm $f_1(\cdot)$ is to transmit its input to its output without any internal processing. Therefore, there is only one output variable z which duplicates the input value x and there are no internal variables. Its internal coordination is then

$$g_c^1 = T(\phi:z) = 0 \quad (21)$$

Since the internal coordination of any nontrivial algorithm (i.e., other than the identity algorithm) is greater than zero, $g_c^i > 0$, it follows that

$$g_c^i > g_c^1 \quad (22)$$

Given that the PP contains a deterministic algorithm without any decisionmaking capability, then

$$H(x) \geq H(x') > 0. \quad (23)$$

According to Eqs. (19a) to (23), the following two inequalities will always be valid.

$$G_{DM_1} > G_{DM_2} \quad (24)$$

$$G_{DM_1} < G_{DM_2} + G_{PP} \quad (25)$$

From the expressions of the total activity within the two DM systems given in Eqs. (15) and (16), the inequalities in Eqs. (24) and (25) show that even though the workload of the first system is less than that of the second system, the presence of the PP makes the workload of the second decisionmaker to be less than that of the first one. This result establishes a preprocessor's ability to reduce the activity of a decisionmaker. Therefore, decision aids that perform part of the situation assessment, e.g., some of the signal processing, are indeed useful devices, because they reduce some of the decisionmaker's processing load.

## THE DUAL-TASK PROBLEM

Another application of the preprocessor is to facilitate a decisionmaker in handling two concurrent tasks. When the measure of performance is properly defined the system performance of the dual-task case can be compared with that of single-task case.

Two variants of the dual-task problem have been investigated (Chyen, 1984). One is the sequential dual-task problem in which inputs of two different tasks arrive one after another in a sequential manner. The other is the parallel dual-task problem in which inputs of the two tasks arrive in parallel in a synchronous manner. For the single-task case, the input arrival rate will be identical to the rate of the dual-task case in order to compare properly the two workloads.

In this section, the sequential dual-task problem in the context of a single decisionmaker aided by a preprocessor will be formulated and then analyzed to determine the effect that executing two non-synergistic tasks can have on system performance.

The model of the sequential dual-task processing shown in Fig. 4 consists of a preprocessor and a decisionmaker.

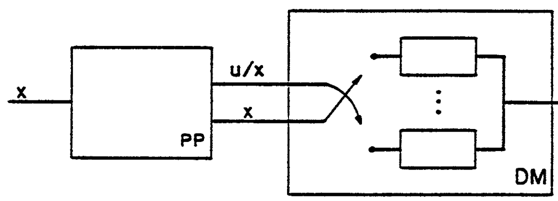


Figure 4. Sequential Dual-Task Processing Model

The input x of the system may be from task A with input alphabet $X_A$, or task B with input alphabet $X_B$. The PP examines each individual input to distinguish the task to which the particular input belongs. If it is a task A input, then the PP will yield a decision strategy $p(u_A)$ pertaining to task A to the DM for processing the input; otherwise strategy $p(u_B)$ pertaining to task B will be generated.

These decision strategies are the variables determining system activity and system performance. A pure or deterministic strategy means that a specific algorithm is always chosen to process the inputs from that particular task. A mixed or stochastic strategy is one obtained as a convex combination of pure strategies. In order to simplify the analysis that follows, it is assumed that there are only two pure strategies available for each individual task. When the four pure strategies of the two tasks are denoted by $u_A^1$, $u_A^2$, $u_B^1$, $u_B^2$, the mixed strategies $u_A$ and $u_B$ of the two tasks can be written as functions of decision strategy parameters $\delta_A$ or $\delta_B$ which correspond to the probabilities of employing pure strategies $u_A^1$ and $u_B^1$ respectively.

$$u_j = \delta_j u_j^1 + (1-\delta_j)u_j^2 \qquad 0 \leq \delta_j \leq 1 \quad j=A,B \quad (26)$$

Again, for the sake of simplicity, only the decision strategies of the SA stage are considered. The situation assessment variable z is the system output.

Given that z' is the desired decision response, the performance J of a decisionmaking task can be defined as the probability of error in determining z. Since two tasks are being performed, their measures of performance $J_A$ and $J_B$ are defined as the probabilities of error in executing task A and task B respectively.

$$J_j = p(z \neq z') | x \epsilon X_j) \qquad j = A,B \qquad (27)$$

If the performance measure, evaluated when a pure strategy is in effect, is denoted by $J^1$ and $J^2$, respectively, then the quantities $J_A$ and $J_B$ can be rewritten as functions of the parameters $\delta_A$ and $\delta_B$ that specify the decision strategies $u_A$ and $u_B$:

$$J_j(\delta_j) = \delta_j J_j^1 + (1-\delta_j)J_j^2 \qquad j = A,B \qquad (28)$$

Now the measure of overall performance for the system can be defined by the probability of making a task A error or a task B error. If $\alpha$ is the probability of the system processing task A inputs, then by assuming errors on both tasks to be equally detrimental the system performance J can be written as

$$J(\alpha) = \alpha\, J_A(\delta_A) + (1-\alpha)J_B(\delta_B) \qquad 0 \leq \alpha \leq 1 \qquad (29)$$

Graphically, for a fixed $\alpha$, the system performance J can be plotted as a tilted plane with boundaries at the planes $\delta_A$=0 and 1 and $\delta_B$=0 and 1. The plane in the 3-dimensional space $(J,\delta_A,\delta_B)$ is shown in Fig. 5.

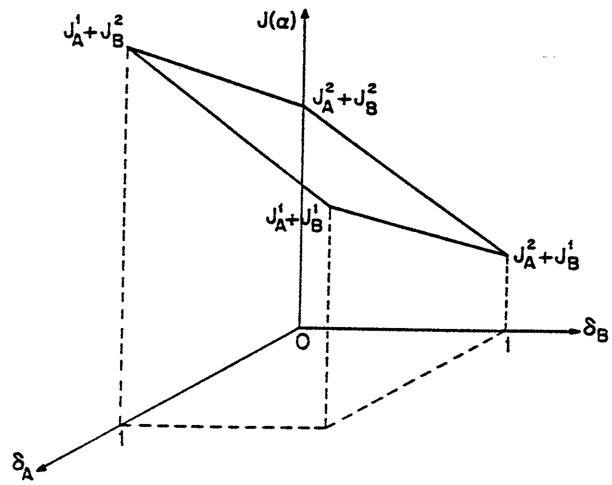


Figure 5. Total Performance Versus Decision Strategy Parameters $\delta_A$ and $\delta_B$

The total activity of the system for single-task processing is a convex function of the decision strategy parameters $\delta_A$ and $\delta_B$, whereas that of dual-task processing is a convex function of the task division parameter $\alpha$ as well as the decision strategy parameters $\delta_A$ and $\delta_B$. The covexity of the system activity G in $\alpha$ as well as in $\delta_A$ and $\delta_B$ has been demonstrated by Hall (1982).

$$G_j(\delta\ ) \geq \delta_j\, G_j^1 + (1-\delta_j)G_j^2 \qquad j = A,B \qquad (30)$$

$$G(\alpha) \geq \alpha\, G_A(\delta_A) + (1-\alpha)G_B(\delta_B) \qquad (31)$$

A typical graph of G for a fixed $\alpha$ is shown in Fig.6.

The system activity or workload in Fig. 6 is a curved bounded surface with four corners (somewhat like a tent). When, for a fixed $\alpha$, J is ploted against G, parametrically with respect to $(\delta_A,\delta_B)$ the performance-workload locus for the whole system can be constructed.

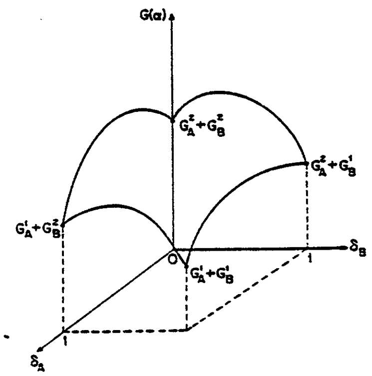


Figure 6. Total Workload Versus Decision Strategy Parameters $\delta_A$ and $\delta_B$

To simplify the construction of the locus, but without any loss of generality, it is assumed that $\delta_A = \delta_B = \delta$, i.e., both task A and task B employ the same rule in decisionmaking (but the content of the decisions may be different). For example, if there are four algorithms $f_1$, $f_2$, $f_3$, and $f_4$ in the DM, the pure strategies of the two tasks can be defined as employing different algorithms. For instance, for task A: $u_A^1$ means u=1; $u_A^2$ means u=2; while for task B: $u_B^1$ means u=3 and $u_B^2$ means u=4. Then the mixed strategies, $u_A$ and $u_B$, will have the same form but different content in the decisionmaking process.

$$u_j = \delta\, u_j^1 + (1-\delta) u_j^2 \qquad j = A,B \qquad (32)$$

With such a formulation, Fig. 6 will degenerate into the 2-dimensional plot shown in Fig. 7.

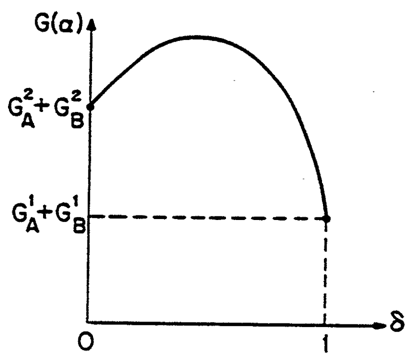


Figure 7. Workload Versus Decision Strategy Parameter δ

Therefore, the J-G plot of the system for a fixed α can be drawn parametrically with respect to δ (Fig. 8).

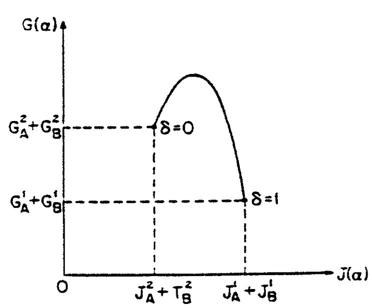


Figure 8. System Workload Performance Locus

If for all the different relative task frequencies, i.e., $0 \leq \alpha \leq 1$, the assumption $\delta_A = \delta_B = \delta$ is always kept, then J-G plots similar to that in Fig. 8 can be drawn for each value of α. To display all these J-G plots in such a format that the performance of single-task processing and dual-task processing can be compared, G can be plotted in a polar coordinate plane with its radial coordinate being the system performance J and the angular coordinate being proportional to the task division parameter α, i.e.,

$$\theta \in [0, \tfrac{\pi}{2}] \qquad \alpha \in [0,1]$$

where $\alpha = (\theta/\pi/2)$.

Therefore, a typical J-G plot of the system for all possible values of α may look like the curved surface in Fig. 9 which resembles part of the surface area of a toroid with curved edges. Its edges at δ=0 and δ=1 are curved upward with respect to G because, for a particular decision strategy, the system activity G is a convex function of the task division parameter α. The other two edges of the curved surface in Fig. 9 are the J-G plots for the single task processing. The projection of the surface on the J-α plane will be a curved area in the shape of a quarter toroid as shown in Fig. 10.

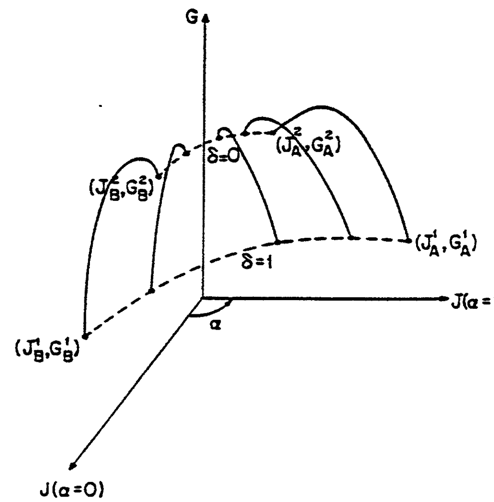


Figure 9. System Workload Performance Loci of Changing Task Division Parameter α.

When the system exhibits bounded rationality behavior, the plane of the activity threshold G may cut through the curved surface in Fig. 9. The surface above the cut corresponds to the region where the workload exceeds the bounded rationality constraint. The remaining surface represents the region with admissible strategies. The projection of the remaining surface on the J-α plane will allow comparison of performance between single-task processing and dual-task processing. Depending on the numerical specifications of the problem, the projection of the region that results from admissible strategies may look like Fig. 11.

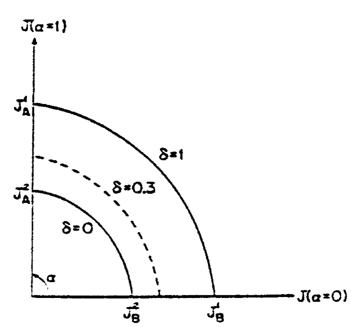


Figure 10. Projection of Fig. 9 on the J-α Plane

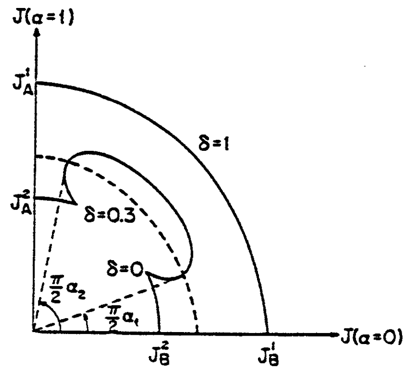


Figure 11. Projection of Locus Due to Admissible Strategies on the J-α plane.

The locus in Fig. 11 is obtained by considering a plane of constant G in Fig. 9 that is above the δ=1 boundary of the $(G, J_A, J_B)$ surface and intersects the δ=0 boundary. This is illustrated in Fig. 12. For δ=0.3, a large central segment of the G-α curve exceeds the threshold level $G_r$. Because of the convexity of the G-α curves, the eliminated segment is defined by the interval $(\alpha_1, \alpha_2)$. Similarly, a segment of the δ=0 curve, the δ=0.6 curve, and the ones for intermediate values of δ, are eliminated. This results in the shape shown in Fig. 11.

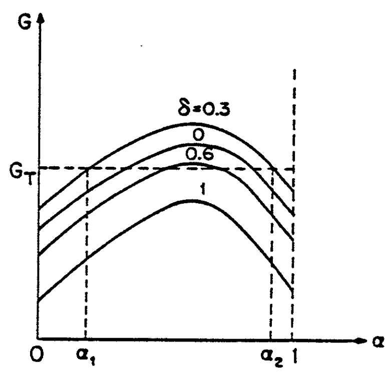


Figure 12. G-α curves for various values of δ

It can be observed in Fig. 11 that under the constraint of bounded rationality ($G \leq G_r$), the decisionmaker doing a single, or almost a single task, achieves a wider range of performance values, including the optimum ones. This is evidenced by the locus near the axes α=0 and α=1. When both tasks have to be carried out, the range of values of the performance is smaller; many of the better values are not achievable. Such a deficiency can be explained by the need for extra time and energy for a decisionmaker to adjust in handling a different task. Hence, in general, a decisionmaker performs better in processing a single task than processing two different tasks in sequence, even though the incoming task rate for both cases are the same. These results, based on the analytical model, are consistent with the experimental results obtained by Kelly and Greitzer (1982) and provide a plausible interpretation for the observed degradation of performance.

## CONCLUSIONS

One of the uses of a preprocessor is to reduce the workload in the situation assessment stage of a decisionmaker by processing the input data.

A preprocessor can also be used to facilitate a decisionmaker in handling a dual-task. Such a preprocessor functions as a matching algorithm to yield appropriate decision strategies for processing two kinds of inputs. It has been shown that a decisionmaker carrying out a dual-task cannot perform any better than when he executes a single task. This is due to the readjustment effort required by the decisionmaker to handle the different, non-synergistic tasks. The analytical results provide an interpretation of recent experimental results.

The main focus of this paper was to present models of preprocessors and methods for their analysis. This constitutes the first step in the development of a mathematical theory and procedures for the design of decision aids. Indeed, several simple necessary conditions have been derived that decision aids must satisfy, if their effect is not to be detrimental to the decisionmaker, i.e., if they are not to cause degradation of a decisionmaker's performance.

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