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PRELIMINARY TEST RESULTS FOR LAYEVAL.(U)
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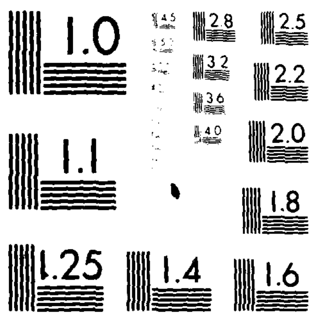

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PRELIMINARY TEST RESULTS

FOR

LAYEVAL

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and Operations Research
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December, 1981

Final Report
Technical Report No. 8
Office of Naval Research
Contract
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DEPARTMENT OF INDUSTRIAL ENGINEERING
AND OPERATIONS RESEARCH
UNIVERSITY OF MASSACHUSETTS, AMHERST

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CONTENTS

1.0 INTRODUCTION

The development of a computer based model for the evaluation of deck plan layouts for the Navy has resulted in the LAYEVAL evaluation system. It represents a procedure for assessing selected importance weights assigned by decision makers in the layout evaluation process. This model is described in detail in [1] and a specification for the computer system appears in [3]. Figure 1 displays the conceptual system and its components. The outlined section contains the essential elements that comprise the LAYEVAL system.

The LAYEVAL system has yet to be thoroughly tested, although preliminary validation efforts have been undertaken and these results are described in this report. It is anticipated that a more complete validation will be conducted in a later effort.

Several experimental directions were explored during the testing of LAYEVAL. These directions were not visible to the surrogate decision-maker (DM) who is shown as the "Designer" in Figure 1. The DM was asked to supply specific information and, later, was shown the weights that resulted from his data. The various data translations and optimization efforts were not displayed to the DM, but these did constitute the areas of exploration for research purposes. The DM interacted with a hard copy questionnaire documented in [2]. The results of this interaction and the experiments on translation and optimization are reported in the later sections of this document. Since the experiments dealt with possible alternative formulations of the mathematical model, it is appropriate to review the model development prior to presenting the results. This next section presents the basic mathematical model with additional details available in [1].

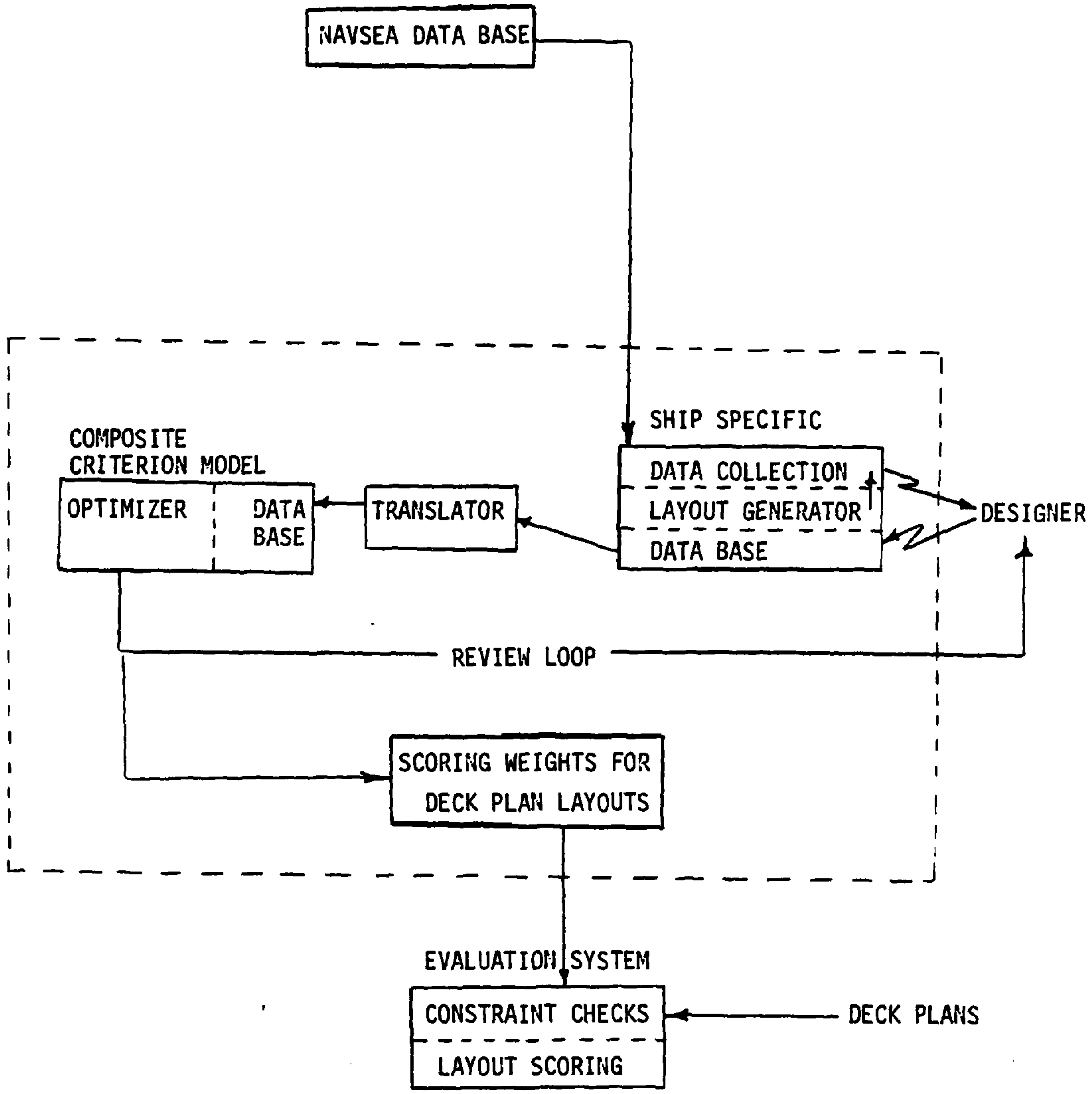

FIGURE 1 : THE LAYEVAL LAYOUT EVALUATION SYSTEM

1.1 REVIEW OF MATHEMATICAL MODEL

LAYEVAL is based upon but significantly different from, a methodology for developing value functions known as the composite criterion model (CCM) formulated by Srinivasan and Shocker [4,5,6]. The CCM is a technique for analyzing a DM's preferences when there are multiple conflicting criteria. In the context of layout evaluation, for the $i^{\underline{th}}$ layout alternative, there is a vector $[a_{ik}]$ of attribute values for $l \epsilon P$, the set of attributes. The score for layout i is:

$$s_i = \nu([a_{ik}]) = \sum_k w_k a_{ik} \tag{1}$$

In the CCM methodology a limited number of explicit pairwise comparisons is used to reveal the proper values of the attribute weights, w_k, for a given decision maker. Note that the value function, $\nu(\ )$, is assumed to be linear.

Given two layout alternatives, i and j, if the DM prefers i over j then $s_i \geq s_j$, i.e.

$$\sum_k w_k a_{ik} - \sum_k w_k a_{jk} \geq 0$$

or (2)

$$\sum_k (a_{ik} - a_{jk}) w_k \geq 0$$

Thus, given a set, Ω, of pairwise layout comparisons, there is a corresponding set of constraints, (2), which must be satisfied by the weights, w_k.

Since it is possible that the DM may err in the preference responses (or that a linear value function assumption is not completely satisfied), the feasible set defined by (2) for $(i, j)\epsilon\Omega$ may be empty. In that case, it is desired to determine a "best" set of weights, i.e. one that comes closest to rationalizing the DM's preferences, where closeness is rigorously defined.

The value measurement problem considering only attribute importance values is to determine the weights, w_k. The CCM provides a means for determining the weights, specifically, (minimizing the sum of the infeasibilities in constraints (2), by solving the following linear programming problem:

$$\text{Minimize} \quad \sum_{(i,\, j)} c_{ij} Z_{ij} \tag{3}$$

$$\text{s.t.} \quad \sum_{k \epsilon P} a_{ijk} w_k + Z_{ij} \geq 0 \text{ for } (i,\, j)\epsilon\Omega \tag{4}$$

$$\sum_{k \epsilon P} \; \sum_{(i,\, j)\epsilon\Omega} c_{ij} a_{ijk} w_k = 1 \tag{5}$$

$$Z_{ij} \geq 0 \quad (i,\, j)\epsilon\Omega \tag{6}$$

$$w_k \geq 0 \quad k\epsilon P_1 \tag{7}$$

$$w_k \leq 0 \quad k\epsilon P_2 \tag{8}$$

$$w_k \text{ urs } k\epsilon P_3 \tag{9}$$

where:

c_{ij} = the confidence coefficient ($c_{ij} \geq 0$) associated by the DM with the paired comparison judgement (i, j).

P = Set of attributes = $P = P_1 \cup P_2 \cup P_3$; $P_i \cap P_j = \emptyset$ for $i \neq j$

$a_{ijk} = a_{ik} - a_{jk}$

The notion of weights in this model includes both the units in which each attribute is scaled and the relative importance (or salience) of each attribute to the individual in the context of his multi-attribute decision-making. The combining of both scale factors and individual measures of salience into weights has been used by other researchers [2].

One difficulty in using the CCM directly for layout evaluation is the potential for an excessive burden upon the DM concerning preferences about entire layouts and the need to express such preferences among many entire layouts. Another problem is that of optimization complexity, considering the larger ship designs developed by the Navy, since direct application of the CCM results in non-linear models and these are difficult to solve in practice. Therefore, LAYEVAL was developed to overcome these difficulties while retaining the essence of the CCM approach.

An important element of LAYEVAL is the decomposition of the layout into smaller elements where activities or compartments become the focus of the DM's attention. With this perspective, two types of attributes are considered. The first category, the <u>intrinsic attributes</u>, attributes that describe the operating conditions of the space and its assigned activity. Temperature, noise and humidity levels are examples of intrinsic attributes. It is further assumed that the operating conditions of a space are primarily affected by operating conditions of spaces near or immediately adjacent to it.

The second category is that of <u>flow attributes</u>. These attributes are distinquished by interactions between specific activities, and the distance between these interacting activities is an important consideration. Material flow, personnel interaction and egress are examples of flow attributes.

Although intrinsic attributes or flow attributes may have continuous measurement scales, it is further conjectured that the DM considers only ranges of the attribute value rather than the exact values. Specific design requirements in some cases may be stated in terms of ranges of these attribute values, but past practice or convention and simply ease of interpretation on the part of the DM may also support this assumption.

Thus the measurable attributes to be considered in the layout evaluation process are assumed to be either intrinsic or flow attributes. Further, it is assumed that the DM is primarily concerned with a discrete number of intervals of attribute values during evaluation. The following sections demonstrate that layout attributes having these characteristics can be accomodated in the CCM methodology in a manner that significantly eases the computational burden.

1.1.1 A VALUE FUNCTION FOR INTRINSIC ATTRIBUTES

Consider an intrinsic attribute such as ambient noise level. For each activity, a, the DM can specify a desired or acceptable attribute level, e.g., very quiet, quiet, moderately noisy, or very noisy. Suppose that for attribute k, there are L_k such intervals or attribute levels, specified by the DM, and that l_k is the desired or acceptable attribute level for activity a on attribute k.

Now consider actvities a and b, adjacent in some layout. If l_k for activity a does not equal l_k for activity b, then one of the activities may not attain its desired or acceptable attribute level. For example, placing a freight elevator next to a conference room doesn't affect the acceptability of the noise level in the freight elevator, but it might lead to an unacceptable or undesirable noise level in the conference room. Thus, for intrinsic attributes, it seems reasonable to focus concern on the differences in target attribute levels between adjacent activities.

From this example, it is clear that attribute differences between adjacent activities are not reflexive, i.e., the difference doesn't matter from the consideration of the freight elevator, while it certainly does matter from the consideration of the conference room. Therefore, if there are L_k attribute levels, then there are $L_k (L_k - 1) + 1$ distinct attribute level difference categories.

Given a specific layout, let $\bar{X}_{akm}$ be the number of activities adjacent to activity a whose specified level of attribute k induces an attribute difference (relative to a's specified level, l_{ak}) in difference category m, $1 \leq m \leq L_k (L_k - 1) + 1$. Then the attribute value function is given by:

$$S_{ak} = \sum_m w_{km} \; X_{akm} \tag{10}$$

This value function permits the comparison of different layouts considering only activity a. The weights y_{ilk} must be determined.

The S_{ak} values must be aggregated in some way to develop an overall score, S_k, for a layout. In aggregating the S_{ak}, not all activities and not all attributes are equally important. For example, the DM may place greater importance on achieving the target noise level in the conference room than he places on achieving the target *in the freight elevator. Therefore, suppose the DM can distinguish* I_k importance levels for attribute k (e.g., unimportant, important, critical). Also, let i_k be the importance attached to the attribute k level for activity a, specified by the DM ($1 \leq i_k \leq I_k$). The definition of I_k and the specification of i_k are for attribute k where k can be either an intrinsic or a flow attribute.

For every activity, a, the DM has specified both l_k, the target attribute level for an intrinsic attribute, and i_k, the importance level associated with achieving that target. The aggregation of the S_{ak} values should reflect these attribute level-importance level pairs. Therefore, define a weight, y_{ilk}, that applies to all activities for which the DM specified attribute level l and importance level i. These weights give numerical values to the DM's interval or level specifications. Then the score for activity a, in a specified layout with only intrinsic attributes, is given by the value function

$$S_a = \sum_k y_{ilk} S_{ak} \tag{11}$$

where $i = i_{ak}$

and $l = l_{ak}$

This value function permits the comparison of different layouts considering only activity a. The weights y_{ilk} must be determined.

1.1.2 A VALUE FUNCTION FOR FLOW ATTIBUTES

While flow and intrinsic attributes are quite different in nature, similar methods can be used for developing their respective attribute value functions. For each type of flow, f, suppose the DM can distinguish L_f distinct levels of interaction and can assign (nonreflexive) interaction levels l_{abf} and l_{baf} for the flows between activities a and b.

If, in a particular layout, D(a,b) is the distance, in any appropriate metric, between activities a and b, then

$$D(a,b)\ l_{baf}$$

is their weighted interaction for flow type f from activity b to activity a. Even within flow type f, all interactions between pairs of activities may not be equally important. As before, suppose the DM can distinguish I_f importance levels for flow type f and assigns the flow interaction l_{baf} to an importance category i_f. The specific weight associated with this importance category is u_{lf} where the values of u_{lf} are to be determined by the model. Thus, the weighted interaction for flow type f from activity b to activity a becomes,

$$u_{lf}\ D(a,b)$$

and the value function for a particular activity a and flow attribute f, considering all other activities, is given by:

$$s_{af} = \sum_{b \neq a} u_{lf}\ D(a,b) \qquad (12)$$

where

$$l = l_{baf}$$

The CCM methodology can be used to determine the weights.

Also, once the weights, u_{lf}, are known, the score for activity a, in a specified layout considering only flow attributes, can be obtained:

$$s_a' = \sum_f y_{ilf} \; s_{af} \tag{13}$$

The y_{ilf} weight, defined previously, relates to the flows themselves in equation (13), while in equation (11) the target differences were important.

1.1.3 A VALUE FUNCTION FOR THE LAYOUT

The weight, y_{ilk}, that applies to all activities for which the DM specified or measured attribute level l and importance level i necessarily involves consideration of each activity and each attribute in its specification. Hence, the relative importance of activities and their attribute levels are normalized through the y_{ilk} variable. Thus, in a manner consistent with the assumption of an additive model, the score for the entire layout can be otained from the following value function:

$$s = \sum_i \sum_{f,k} (y_{ilk} \; s_{ak} + y_{ilf} \; s_{af}) \tag{14}$$

2.0 BACKGROUND

The model described in the previous section was tested in the context of ship layouts. The DM for this case was a volunteer graduate student studying ship arrangement design who had previously served in the Navy. Initially, the questionnaire was administered to three volunteer graduate students. Only two of the questionnaires were returned. Of the two, one seemed to have responses that failed to follow directions and definitions. Hence, it was not used to test the model.

The limited amount of the volunteer DM's available time necessitated the use of a small hypothetical ship consisting of 26 activities and 6 decks for this study. Since multiple decks were considered, the problem was three dimensional.

Discussion with personnel at the Naval Sea Systems Command helped to decide on the activities to be included in the layout design, as well as a potential set of attributes to be considered in evaluating the alternate designs. A set of requirements to be satisfied was also provided by the Navy personnel and this enabled the generation of four layouts for comparison. Each layout should have been acceptable to the DM, thus permitting evaluation based on the attributes considered. As indicated earlier, the details of the layouts and the questionnaire appear in Report No. 5 [1].

Two interaction sessions were held with the DM, the first of about six working hours was used to explain the model to the DM, to discuss the attributes used for evaluation, and to obtain the responses necessary for determining the unknown weights (variables) of the model.

Because of the limited interaction time available, only three intrinsic attributes (noise, temperature, and humidity), and two flow attributes (nearness to desired decks and functional performance) were selected.

The second session of about two hours was used to discuss the results obtained from the first session responses and to uncover the causes for some unexpected results displayed by the model solutions. In the first session, the DM was directed to the appropriate sections of the questionnaire and the questions were fully explained. Members of the research team were always available during the session for any additional clarification.

The Multiple Purpose Optimization System (MPOS) package from Northwestern University was used to obtain the solution to the optimization problems (necessary in the stages of LAYEVAL), on the CDC Cyber 70 series computer of the University of Massachusetts. Solution times were of the order of 5-15 seconds, including compilation and execution times, and thus the model appears to be quite efficient in the use of computing resources.

Table I displays the expressed preferences by the DM for the levels of intrinsic attributes and the layout activities. The individual entries in the Table reflect both the specification of preference and the confidence with which the DM held the preference. Table II displays similar data for the preferences for layouts expressed by the DM when considering all attributes combined. The indication of Stage 1 and Stage 2 refers to the phases of the LAYEVAL solution procedure in which these data utilized. The flow attribute data was not used for reasons to be developed later.

TABLE I: PREFERENCE RESPONSES (Stage 1)

Compartments	INTRINSIC ATTRIBUTES																	
	NOISE Layout Pairs						TEMPERATURE Layout Pairs						HUMIDITY Layout Pairs					
	A B	B C	C D	A C	A D	B D	A B	B C	C D	A C	A D	B D	A B	B C	C D	A C	A D	B D
1	1,1	2,1	1,2	2,1	2,1	2,1	1,1	2,1	2,2	2,2	2,1	2,1	1,1	2,1	2,2	2,2	2,1	2,1
2	1,1	2,1	1,1	2,2	1,1	2,2	1,1	2,1	1,2	2,2	1,3	2,1	1,1	2,1	1,2	2,2	1,3	2,1
3	1,1	2,1	1,2	1,2	1,1	2,2	1,1	2,1	1,2	1,2	1,1	2,1	1,1	2,1	1,2	1,2	1,1	2,1
4	1,1	2,1	1,1	2,2	1,1	1,2	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3
5	2,1	1,1	1,1	1,1	1,1	1,1	2,2	1,1	1,1	1,2	1,1	1,1	2,2	1,1	1,1	1,2	1,1	1,1
6	1,3	1,3	2,3	1,3	2,3	2,3	1,3	1,3	2,3	1,3	1,3	1,3	1,3	1,3	2,3	1,3	1,3	1,3
7	2,3	2,2	2,3	2,2	2,2	2,2	2,1	2,2	1,3	2,1	2,1	2,2	2,2	2,3	1,3	2,2	2,2	2,3
8	1,1	2,1	1,2	2,3	1,2	2,1	1,1	2,1	1,1	2,2	1,2	2,1	1,1	2,1	1,1	2,2	1,2	2,1
9	1,3	1,1	1,1	1,1	1,1	1,1	2,2	1,1	1,1	1,2	1,1	1,1	2,2	1,1	1,1	1,2	1,1	1,1
10	2,2	1,3	1,1	2,2	1,1	1,1	2,2	1,3	1,1	2,2	1,1	1,1	2,2	1,3	1,1	2,2	1,1	1,1
11	1,3	1,2	1,1	1,2	1,1	1,1	1,3	1,3	1,1	1,3	1,1	1,1	1,3	1,3	1,1	1,3	1,1	1,1
12	1,1	2,1	1,2	1,2	1,1	2,2	1,2	2,1	1,3	2,2	2,2	2,1	1,2	2,1	1,3	2,2	2,2	2,1
13	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,1	1,3	1,1	1,1	1,3	1,3	1,3	1,3	1,3	1,3
14	1,3	1,3	1,3	1,3	1,3	1,3	1,2	2,2	2,2	1,3	2,2	2,1	1,3	2,3	2,3	1,3	2,3	2,3
15	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,2	2,1	1,2	2,1	2,1	1,3	1,2	2,1	1,2	2,1	2,1
16	1,1	1,3	2,1	1,1	2,2	2,1	1,3	1,3	2,3	1,3	2,3	2,3	1,1	1,1	2,1	1,1	2,3	2,1
17	1,3	1,3	1,3	1,3	1,3	1,3	1,1	2,2	2,1	1,1	2,3	2,1	1,1	2,2	2,1	1,1	2,3	2,1
18	1,3	2,2	2,2	2,2	2,1	2,1	1,2	2,1	2,2	2,1	2,1	2,1	1,2	2,1	2,2	2,1	2,1	2,1
19	1,3	1,3	1,2	1,3	1,2	1,2	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3	1,3
20	1,1	2,1	1,2	1,3	1,2	2,1	1,1	2,1	1,3	1,3	1,3	2,1	1,2	2,2	1,3	1,3	1,3	2,2
21	2,1	1,2	2,3	2,1	2,1	1,2	2,1	1,2	2,3	2,1	2,1	1,2	2,1	1,2	2,3	2,1	2,1	1,2

Note: Entry 1,2 indicates that the first layout of the pair (hence 1) is preferred with confidence level 2.
Confidence Level 1: Certain
2: Reasonably sure
3: Unsure

TABLE II: PREFERENCE RESPONSES (Stage 2)

ALL ATTRIBUTES

Layout Pairs

COMPARTMENTS	AB	BC	CD	AC	AD	BD
1	1,2	2,2	1,1	2,3	1,1	1,1
2	1,1	2,1	1,1	2,2	1,1	2,1
3	2,2	1,1	2,3	1,2	1,2	1,1
4	1,3	1,3	1,3	1,3	1,3	1,3
5	2,1	2,2	2,3	2,1	2,1	2,2
6	1,3	1,3	2,3	1,3	1,3	1,3
7	2,3	2,1	1,2	2,1	2,1	2,1
8	1,1	2,1	1,1	1,3	1,1	2,2
9	1,3	2,1	1,2	2,1	2,1	2,1
10	1,3	2,1	1,2	2,1	2,2	2,2
11	1,1	2,1	1,2	2,2	1,3	2,1
12	1,2	1,3	1,3	1,2	1,2	1,3
13	2,3	2,2	2,2	2,2	2,1	2,1
14	1,1	1,3	2,1	1,1	1,2	2,1
15	1,1	1,1	2,1	1,1	1,1	2,2
16	1,1	1,3	2,1	1,1	2,1	2,1
17	2,2	1,1	2,2	1,2	1,3	1,2
18	1,1	2,2	1,1	1,2	1,1	1,1
19	1,3	1,3	1,3	1,3	1,3	1,3
20	1,2	2,2	1,3	1,3	1,3	2,2
21	2,1	1,1	2,3	2,1	2,1	1,1

Note: Entry 1,2 indicates that the first layout of the pair (level 1) is preferred with confidence level 2.
Confidence Level 1: Certain
2: Reasonably Sure
3: Unsure

3.0 BASIS FOR TESTS

Since the DM was not forced to make comparison judgments, but could choose to be indifferent between alternatives or choose not to answer by indicating an "unsure" level of confidence in the responses, the forced choice model which used equation (2) as the constraints was inappropriate. "unsure" responses were dropped from the constraint set and the constraints were generated by the following inequality:

$$\sum_k (a_{ik} - a_{jk})\, w_k \geq d \tag{15}$$

where d is an arbitrarily small positive number

If all responses were at "unsure" confidence levels, no constraints can be generated and the variables must be obtained using a modified version of LAYEVAL. It is then important to distinguish between two cases. The DM indicating "unsure" confidence levels because he/she, i) did not want to make a preference decision, and was not forced to make it, or ii) was sure that the alternatives were very similar, and hence was indifferent between them. In the first case, the DM has not expressed any preference at all hence his preferences cannot be quantified by means of determining the weights. In the second case, indifference between alternatives A and B can generate two inequalities in the model corresponding to A preferred to B, and B preferred to A, in the manner described by Srinivasan and Shocker [5,6]. For this test, the distinction between the above two cases was not made, hence the "unsure" responses were not used in the constraint set.

The value of d was determined from:

$$M \times d = 1.0 \tag{16}$$

Where M = number of ordered pairs for which j is strictly preferred to k

The remaining confidence coefficients, c_{ij}, associated with "certain" and "reasonably sure" responses were utilized in several ways. In one instance they were set at the arbitrary values 2 and 1 respectively. In this instance, it was felt that the difference in confidence should somehow influence the determination of weights so that the weights would favor the satisfaction of the inequalities generated by the "certain" preferences over the inequalities generated by the "reasonably sure" preferences. However, the choice of values for the confidence coefficients is subjective and hence not defensible. Therefore, for the second instance, another set of results was obtained where the "certain" and "reasonably sure" responses were weighted equally.

At the second stage of the model it was noticed that the coefficients associated with the y_{ilk} in the constraints, using the scaled weights of stage one, were generally much smaller than those associated with the y_{ilf}. The measurement scale for the flow attributes was therefore increased by a factor of 20 (that is, the coefficients of y_{ilf} were divided by 20) in order to have coefficients of about the same scale for each attribute. This scaling was done only to permit a better visual assessment of the coefficients. It was not required. All it means, in operational terms, is that distances should be measured in units of 20 basic building blocks rather than in units of basic building blocks, and the choice of distance metric could resolve this.

Also, at the second stage of the model, it was assumed that when the DM was asked to indicate in which of two layouts he preferred the position of a specific activity, considering the positions of other activities, and considering <u>all attributes simultaneously</u>, he would take into account only those attributes for which he had been able to indicate a definite preference at the individual attribute level. For example, if a definite preference was expressed considering the attribute noise, and a definite preference was expressed considering the temperature, but the DM could not express a preference (or expressed a preference at the "unsure" confidence level) with respect to other attributes, then when the DM expressed an overall preference, it was assumed that he/she would focus his attention only on the attributes noise and temperature and ignore the other attributes.

This assumption is consistent with the indication by the DM that he tended to focus more on the very different, or extreme conditions and ignored the similar, or average conditions. In the preceding example this would mean that the constraint generated by the expressed overall preference at the second stage would include only the variables associated with the noise and temperature attributes. It is again theoretically possible that the subscore with respect to a specific attribute is at the "unsure" confidence level for every constraint, thereby implying that the variables associated with the attribute at the second stage cannot be determined. In this case, although the attribute may be important, it cannot help to differentiate among alternatives, hence it is unimportant for prediction purposes.

An assumption commonly made when evaluating layouts is that costs, or values, vary linearly with distance. An attempt was made in this case study to determine if the assumption was justified. In a preliminary analysis, the responses to one section of the questionnaire indicated that the DM's values varied almost linearly with distance. Therefore, a detailed study of the variations of value with distance was not pursued. It must be noted that the analysis was restricted to the 5 - 50 foot distance range. It is conceivable that nonlinearities would be noticed if wider ranges were considered.

4.0 RESULTS

The numerical results from the optimization process are reported in two major categories representing the experimental options on the confidence coefficients. The first set of results are for the c_{ij} values of "certain" and "reasonably sure" set arbitrarily at 2 and 1 respectively. The second set of results are where no distinction between "certain" and "reasonably sure" is made, i.e. the c_{ij} values are set at 1 and 1.

Within each category of results, two stages of values corresponding to the stages of optimization implied by (10) and (12) for stage 1 and (14) for stage 2 are reported. Thus, one could view the stage 1 results as related to individual attribute levels and the stage 2 results as displaying the weights between attributes.

Returning to the CCM methodology described in section 1.1, for two layout alternatives, i and j, an expressed preference by the DM for i over j implies that $s_i \geq s_j$. Should the calculated weights, when recombined into a score, actually give $s_i \geq s_j$ this would be considered desirable. However, if the calculated weights give $s_j > s_i$ then the estimated weights are not in conformance with the DM paired comparisons and a measure of goodness of fit for the predicted weights can be developed as described below.

Since a calculated s_i greater than or equal to s_j based upon the weights matches the DM's preferences, the following term can be defined:

$$(s_i - s_j)^- = \begin{cases} 0 \text{ if } s_i \geq s_j \\ (s_j - s_i) \text{ if } s_j > s_i \end{cases} \tag{17}$$

or

$$(s_i - s_j)^- = \max\,[0,\ (s_j - s_i)] \tag{18}$$

Thus $(s_i - s_j)^-$ is a measure of error corresponding to the layouts i and j and a given solution to the weights. Considering all of the layouts in Ω (from (2)), define the following:

$$B = \sum_{(i,j) \in \Omega} (s_i - s_j)^- \tag{19}$$

as a measure of poorness of fit for the calculated weights over the set of layouts, Ω, for which preference data was expressed. It is desirable to minimize B.

Unfortunately, B can be minimized in a trivial fashion by simply having all weights equal zero. Then $s_i = s_j = 0$, still satisfying $s_i \geq s_j$. This type of solution yields no useful information and a modified approach to the problem must be taken. Inequality (15) considered a small positive difference, d, for the attributes' score for layouts i and j. This required difference over all layouts in Ω can be defined as h where:

$$\sum_{(i,j) \in \Omega} (s_i - s_j) = h \tag{20}$$

and h is an arbitrary positive constant that merely serves as a scaling factor. A new index of fit can now be defined as:

$$C = \frac{B}{h + B} \tag{21}$$

where C is bounded by 0 and 1. Now any solution, other than the trivial solution of zero weights, that optimized B will also optimize C. It is therefore desirable to minimize C and the C values are displayed in all results.

4.1 RESULTS FOR UNEQUAL CONFIDENCE COEFFICIENTS

It should be recalled that the confidence coefficients for the following results were arbitrarily set at a value of 2 for "certain" and a value of 1 for "reasonably sure" in analyses based on the comparisons shown in Table I.

4.1.1 STAGE 1 RESULTS

The calculated weights for the attribute noise appear in Table III.

Table III

Results for the attribute <u>Noise</u> with confidence coefficients of 2 and 1 (stage 1)

Unknown Variables	W_{11}	W_{12}	W_{13}	W_{14}	W_{15}	W_{16}	W_{17}	W_{18}	W_{19}
Numerical Weights	4.967	8.558	10.144	0.	.188	.698	2.982	2.664	3.335
Scaled Weights (1)	.21	.36	.43	0.	.21	.79	.33	.30	.37
Objective function value		0			44.5			3.8	
Index of fit, C		0			.31			.04	
Number of correctly predicted preferences (2)		9(4+5)			26(19+7)			22(14+8)	
Number of wrongly predicted preferences (2)		0(0+0)			17(10+7)			4(1+3)	
Overall number of preferences correctly predicted by weights (2)					57(37+20)				
Overall number of preferences wrongly predicted by weights (2)					21(11+10)				
Overall number of preferences indicated (at other than the unsure confidence level) (2)					78(48+30)				

(1) scaled so that the weights of the separate subproblems sum to one.

(2) (n+m) means that n were expressed at the "certain" level of confidence, and m were expressed at the "reasonably sure" level of confidence.

Considering the scaled weights in the first block associated with W_{11} W_{12} and W_{13}, it is noticed that the weights increase with m. This appears reasonable since, in general, lower noise levels are preferred (and scores were defined so that lower weights indicate lower penalties). The same situation is noticed with respect to W_{14}, W_{15} and W_{16}. The weights associated with W_{17}, W_{18} and W_{19} are, however, almost the same, indicating that they would, in general, not be very helpful in predicting preferences. The DM agreed with this interpretation at the second interaction session with him, since in his opinion, if an activity had a high noise level, the noise level of adjacent activities could do little to improve or worsen the situation anyway.

The index of fit is good for the first three and the last three but not very good for the middle three. One reason for the poorer fit, indicated by the DM, was that he tended to focus more on quiet activities to ensure that their performance was not affected by noisy neighbors, and on noisy activities to check which activities around them were being affected by the noise. The DM tended to ignore activities at the medium noise levels since their levels could be more easily controlled (by soundproofing) if this was desired, at the final ship design stage. Another reason is that although the index of fit as defined in (21), is claimed by Srinivasan and Shocker to be largely independent of the number of constraints in the constraint set, it is likely that better fits are obtained with fewer constraints at the expense of providing worse e·timates of the weights.

Similar inferences for the attributes temperature and humidity may by drawn from the results presented in Tables IV and V.

Table IV

Results for the attribute Temperature with confidence coefficients of 2 and 1 (stage 1)

Unknown Variables	W_{21}	W_{22}	W_{23}	W_{24}	W_{25}	W_{26}	W_{27}	W_{28}	W_{29}
Numerical Weights	1.729	0.	2.626	1.237	0.	.156	0.	1.814	2.738
Scaled Weights (1)	.4	.0	.6	.89	.0	.11	.0	.4	.6
Objective function value		5.4			26.9			1.0	
Index of fit, C		.05			.21			.01	
Number of correctly predicted preferences (2)		11(7+4)			44(31+13)			11(7+4)	
Number of wrongly predicted preferences (2)		2(0+2)			13(8+5)			1(0+1)	
Overall number of preferences correctly predicted by weights (2)					66(45+21)				
Overall number of preferences *wrongly predicted by weights* (2)					16(8+8)				
Overall number of preference indicated (at other than the unsure confidence level) (2)					82(53+29)				

(1) *scaled so that the weights of the separate* subproblems sum to one.

(2) (n+m) means that n were expressed at the "certain" level of confidence, and m were expressed at the "reasonably sure" level of confidence.

Table V

Results for the attribute Humidity with confidence coefficients of 2 and 1 (stage 1)

Unknown Variables	W_{31}	W_{32}	W_{33}	W_{34}
Numerical Weights	0.	.966	0.	1.562
Scaled WEights (1)	0	1.0	0.	1.
Objective function value	156.9		94.1	
Index of fit, C	.61		.48	
Number of correctly predicted preferences (2)	33(21+12)		20(12+8)	
Number of wrongly predicted preferences (2)	18(12+6)		7(5+2)	
Overall number of preferences corrently predicted by weights (2)	53(33+20)			
Overall number of preferences wrongly predicted by weights (2)	25(17+8)			
Overall number of preferences indicated (at other than the unsure confidence level) (2)	78(50+28)			

(1) scaled so that the weights of the separate subproblems sum to one.

(2) (n+m) means that n were expressed at the "certain" level of confidence, and m were expressed at the "reasonably sure" level of confidence.

In Table V, the weights indicate that the lower humidity level is preferred. The DM agreed with this interpretation. The indices of fit were not as good as those for noise and temperature, possibly due to the fewer levels used for this attribute. The two levels result in four variables used to account for the preferences indicated by the DM. For noise and temperature, the three levels allowed for nine variables.

4.1.2 STAGE 2 RESULTS

The second stage results reported in Table VI were also scaled in the manner described in the preceding section for the first stage. These data were scaled so that the variables summed to thirty. Although the scaling is not required technically, the arbitrary value to thirty was chosen to permit a better visual assessment.

In Table VI, it is instructive to consider the variables associated with the first three data columns separately from those associated with the last three data columns for intrinsic attributes and the first data column separate from the latter data columns for flow attributes. As a group the former are associated with low levels of functional (or flow attribute) connection between activities, and cases where it is less important that activities have compatible neighbors (in the sense of intrinsic attribute levels). It is observed that only three out of the ten variables in this first group are at positive levels. Obtaining zero weights for these variables appears reasonable.

Table VI

Second stage results with confidence coefficients of 2 and 1 and d = .00124

Noise

Unknown variables	y_{111}	y_{121}	y_{131}	y_{211}	y_{221}	y_{231}
Numerical Weights	0.	0.	0.	.02867	.00043	.0
Scaled Weights	0.	0.	0.	.44	.007	.0

Temperature

Unknown variables	y_{112}	y_{122}	y_{132}	y_{212}	y_{222}	y_{232}
Numerical weights	.02054	.00043	.0	.04462	.00393	.0
Scaled weights	.318	.007	.0	.69	.061	.0

Humidity

Unknown variables	y_{113}	y_{123}	y_{213}	y_{223}
Numerical weights	.0	.00225	.0025	1.45142
Scaled weights	.0	.035	.039	22.447

Nearness to desired deck

Unknown variables	y_{114}	y_{214}
Numerical weights	.0	.33377
Scaled weights	.0	5.162

Functional Performance

Unknown variables	y_{115}	y_{215}	y_{315}
Numerical weights	.0	.0	.05127
Scaled weights	.0	.0	.793

Objective function value	.91
Index of fit, C	.01
Overall number of preferences correctly predicted by weights (2)	66(43+23)
Overall number of preferences wrongly predicted by weights (2)	21(12+9)
Overall number of preferences Indicated (at other than the unsure confidence level) (2)	87(55+32)

(1) scaled so that the weights sum to 30

(2) (n+m) means that n were expressed at the "certain" level of confidence, and m were expressed at the "reasonably sure" level of confidence.

since the zero weights imply no penalty for adverse conditions when the DM has indicated that in the particular situation the conditions are only moderately important or not important. Also note that the three positive variables are numerically smaller than their counterparts in the second group that are greater than zero. This is also a reasonable result since higher penalties should be assigned to adverse conditions when the DM has indicated that it is important to have good conditions.

Consider the variables associated with the second group that have values greater than one. These correspond to situations in which it has been indicated that adverse conditions should be penalized. It is observed that only three of the eleven variables are at zero levels. This is an encouraging result considering that two of them, y_{231} and y_{232}, were expected to be zero in accordance with the DM's preference structure. These two variables are associated with activities which are at high levels on the attributes noise and temperature. It was indicated by the DM that it matters little in these cases what the neighboring activities are. The problem of high noise and temperature levels must be solved by controlling the interval characteristics of the activities rather than trying to reduce the levels by surrounding them with activities at low noise and temperature levels.

The zero weight assigned to y_{215} was considered extremely unusual by the DM. The DM considered the second flow attribute to be very important in determining the overall preferences for the activities, whereas the zero weight meant that the second level of this important attribute was not being used by the model to predict preferences.

In order to reconcile this discrepancy, checks were made at the individual attribute level. At the first session, the DM had been asked to predict preferences between activities in paired layouts while considering only the second flow attribute (this set of preferences was not necessary to determine the weights). It was noticed that the weights obtained did not predict these preferences well. An examination of the raw data for the expressed preferences revealed that, in some cases, dominated alternatives were preferred by the DM. Therefore at the second session, the DM was asked to explain his reasoning for the selection of the preferred alternatives, while considering only the second flow attribute.

It was then discovered that a major factor, related to the social structure within a ship, had not been considered. The DM indicated that the revised input would result in a table "with a liberal use of negative entries." The crew, the officers, and the captain constituted three social levels within a ship, making their locations on separate decks desirable, especially with respect to eating, living and recreation areas. The desire was, in some cases, strong enough to constitute a requirement, meaning that a layout design could be rejected based on a single unacceptable situation. This "social structure" attribute was not expressly included by the Navy ship design personnel as an appropriate attribute and hence not discussed with the DM when preferences were elicited from him. It was also not considered when designing the four layouts used for preference judgments. This resulted in some infeasible layouts (considering this attribute), thus violating an important assumption of the model that all layouts must at least be at an acceptable level with respect to requirements (or be feasible) before preference questions are asked to measure values for attibutes.

Such violated requirements have a serious impact on the ability of the model to correctly predict preferences for entire layouts. A layout could be much better than another in every way but could be rejected (and hence not preferred over the other) based on only one violated requirement.

The violation of the requirements does not however invalidate the conclusions drawn earlier. As long as the violations are more the exception rather than the rule, the numerical values assigned to the variables should remain reasonable. But the violations will tend to increase the mismatch between preferences predicted by the model and the preferences expressed by the DM since it will in general be difficult to satisfy the inequalities generated by the preferences which result from requirement violations. Also, the burden of "explaining" the preferences due to the omitted attribute will fall on the included attributes, thereby tending to move the estimates of the variables associated with the included attributes away from their "true values."

There is a tendency for the model to "weigh more," in the sense of better estimate, the variables associated with the columns which are dense. The numerical values of the variables associated with the sparse columns would be more sensitive to changes in parameters. For this small case study some attribute levels were dropped from consideration, since not enough inequalities of the form in (15) could be generated to obtain the numerical weights of the associated variables with any degree of confidence. The preference questions were asked about all activities in order to obtain the weights. Therefore the sparseness of the columns associated with the variables could not be controlled. It was a function of how the activities were classified along attributes. Hence some variables were "weighted" more than others simply because the variables appeared more frequently and hence their columns were denser. When studies are conducted for cases which have many more activities (i.e., large ship designs), then it may be possible to select only a subset of activities about which preference questions are asked to generate constraints, and this selection could be made such that the resulting columns associated with the variables are (approximately) equally dense.

One last observation reguarding the weights in Table VI is that the scaled numerical values of y_{223} and y_{214} are "unusually high." Note that judgments regarding the significance of the attributes should not be made from the numerical values associated with the variables. These values get affected by the scales of measurement used for the attributes. The comments regarding the weights should be, and have been restricted to comparisons of weights within attributes. The only absolute value about which comments have been made, have been the zero numerical values associated with some of the variables, implying that the variables are insignificant.

One possible explanation for the "high" value of y_{214} is that in this test, it was noticed at the second stage that the coefficients associated with the intrinsic attribute, using the scaled weights of stage one, were generally much smaller than those associated with the flow attributes. The measurement scales for the flow attributes were therefore increased by a factor of 20 in order to have coefficients of about the same scale for each attribute. Had this not been done, the numerical value of y_{214} would have been 5.152/20 = .2581 instead.

This scaling was done only for easier visual assessment of the coefficients. It was not necessary and, as mentioned earlier, it does not reflect the significance of the attributes.

There is however a different factor possibly responsible for the high numerical value assigned to y_{223}. Consider the column of a variable in the constraint matrix generated by (15). If the column has only one non-zero entry and this entry is negative (say), then for the case where the inequality associated with the row of that entry is not satisfied by the assigned weights, a unit increase in the variable will increase the objective by the coefficient of the negative entry. If there were ten such entries, then the objective would increase by the sum of their coefficients. There is therefore a tendency for the model to "weigh more," in the sense of better estimate, the variables associated with the columns which are dense. The numerical values of the variables associated with the sparse columns would be more sensitive to changes in parameters. There is only one activity, activity 18, associated with y_{223} and hence its column is sparse. This could have resulted in greater instability, and hence the "high" value. The argument might be used for dropping some attribute levels from consideration, since not enough inequalities of the form in (15) could be generated to obtain the numerical weights of the associated variables with any degree of confidence.

Examining parametrically over values of d (see Tables VII and VIII, it was noticed that the results are quite insensitive to the choice of "d." Increasing d parametrically by more than 2000% over the recommended value did not affect the number of correctly predicted preferences. Based on this limited experimentation, it therefore appears that the predictive power of the model is quite insensitive to the choice of d.

Table VII

Second stage results with confidence coefficients of 2 and 1 and d = .05

Noise

Unknown variables	y_{111}	y_{121}	y_{131}	y_{211}	y_{222}	y_{231}
Numerical Weights	.0	.0	.0	.12743	.00191	.0
Scaled Weights	.0	.0	.0	1.053	.016	.0

Temperature

Unknown variables	y_{112}	y_{122}	y_{132}	y_{212}	y_{222}	y_{232}
Numerical weights	.09138	.00191	.0	.19848	.01748	.0
Scaled weights	.755	.015	.0	1.64	.144	.0

Humidity

Unknown variables	y_{113}	y_{123}	y_{213}	y_{223}
Numerical weights	.0	.01	.01112	1.45882
Scaled weights	.0	.083	.092	12.052

Nearness to desired deck

Unknown variables	y_{114}	y_{214}
Numerical weights	.0	1.48475
Scaled weights	.0	12.266

Functional Performance

Unknown variables	y_{115}	y_{215}	y_{315}
Numerical weights	.0	.0	.22809
Scaled weights	.0	.0	1.884

Objective function value	4.05
Index of fit, C	.0
Overall number of preferences correctly predicted by weights (2)	66(43+23
Overall number of preferences wrongly predicted by weights (2)	21(12+9
Overall number of preferences indicated (at other than the unsure confidence level) (2)	87(55+32

(1) scaled so that the weights sum to 30

(2) (n+m) means that n were expressed at the "certain" level of confidence, and m were expressed at the "reasonably sure" level of confidence.

Table VII

Second stage results with confidence coefficients of 2 and 1 and d = .25

Noise

Unknown variables	y_{111}	y_{121}	y_{131}	y_{211}	y_{222}	y_{231}
Numerical Weights	.0	.0	.0	7.47599	.00953	.0
Scaled Weights	.0	.0	.0	12.112	.015	.0

Temperature

Unknown variables	y_{112}	y_{122}	y_{132}	y_{212}	y_{222}	y_{231}
Numerical weights	.0	.00954	.0	.99238	.08742	.0
Scaled weights	.0	.15	.0	1.608	.42	.0

Humidity

Unknown variables	y_{113}	y_{123}	y_{213}	y_{223}
Numerical weights	.0	.05	.05561	1.29871
Scaled weights	.0	.081	.09	2.104

Nearness to desired deck

Unknown variables	y_{114}	y_{214}
Numerical weights	.0	7.42376
Scaled weights	.0	12.027

Functional Performance

Unknown variables	y_{115}	y_{215}	y_{315}
Numerical weights	.0	.0	1.14043
Scaled weights	.0	.0	1.848

Objective function value	20.24
Index of fit, C	.17
Overall number of preferences correctly predicted by weights (2)	66(43+23)
Overall number of preferences wrongly predicted by weights (2)	21(12+9)
Overall number of preferences indicated (at other than the unsure confidence level) (2)	87(55+32)

(1) scaled so that the weights sum to 30

(2) (n+m) means that n were expressed at the "certain" level of confidence, and m were expressed at the "reasonably sure" level of confidence.

4.2 RESULTS FOR EQUAL CONFIDENCE COEFFICIENTS

For these data, the confidence coefficients were arbitrarily set at 1 for "certain" and 1 for "reasonably sure." Hence both degrees of certainty carried equal weight within the mathematical model.

4.2.1 STAGE 1 RESULTS

The calculated weights for the intrinsic attributes of Noise, Temperature and Humidity appear in Tables VIII, IX and X respectively.

Table VIII

Results for the attribute Noise with
confidence coefficients of 1 and 1 (stage 1)

Unknown Variables	w_{11}	w_{12}	w_{13}	w_{14}	w_{15}	w_{16}	w_{17}	w_{18}	w_{19}
Numerical Weights	7.452	12.832	15.213	0.	.005	1.101	5.273	4.701	5.981
Scaled Weights (1)	.21	.36	.43	0.	.01	.99	.33	.30	.37
Objective function value		0.			46.64			4.897	
Index of fit, C		0.			.33			.05	
Number of correctly predicted preferences (2)		9(4+5)			27(19+8)			22(14+8)	
Number of wrongly predicted preferences (2)		0(0+0)			16(10+6)			4(1+3)	
Overall number of preferences correctly predicted by weights (2)					58(37+21)				
Overall number of preferences wrongly predicted by weights (2)					20(11+9)				
Overall number of preferences indicated (at other than the unsure confidence level) (2)					78(48+30)				

(1) scaled so that the weights of the separate subproblems sum to one.

(2) (n+m) means that n were expressed at the "certain" level of confidence, and m were expressed at the "reasonably sure" level of confidence.

Table IX

Results for the attribute Temperature with
confidence coefficients of 1 and 1 (stage 1)

Unknown Variables	w_{21}	w_{22}	w_{23}	w_{24}	w_{25}	w_{26}	w_{27}	w_{28}	w_{29}
Numerical Weights	2.671	.0	4.04	1.512	.0	.51	.0	3.508	5.28
Scaled Weights (1)	.40	.0	.5	.75	.0	.25	.0	.40	.6
Objective function value		8.213			34.753			1.843	
Index of fit, C		.07			.26			.02	
Number of correctly predicted preferences (2)		11(7+4)			45(31+14)			11(7+4)	
Number of wrongly predicted preferences (2)		2(0+2)			12(8+4)			.(0+1)	
Overall number of preferences correctly predicted by weights (2)					67(45+22)				
Overall number of preferences wrongly predicted by weights (2)					15(8+7)				
Overall number of preferences indicated (at other than the unsure confidence level((2)					82(53+29)				

(1) scaled so that the weight of the separate subproblems sum to one.

(2) (n+m) means that n were expressed at the "certain" level of confidence, and m were expressed at the "reasonably sure" level of confidence.

Table X

Results for the attribute Humidity with confidence coefficients of 1 and 1 (stage 1)

Unknown Variables	w_{31}	w_{32}	w_{33}	w_{34}
Numerical Weights	.0	2.019	.0	2.194
Scaled Weights (1)	.0	1.0	.0	1.0
Objective function value	190.17		74.84	
Index of fit, C	.66		.43	
Number of correctly predicted preferences (2)	33(21+12)		20(12+8)	
Number of wrongly predicted preferences (2)	18(12+6)		7(5+2)	

Overall number of preferences correctly predicted by weights (2)	53(33+20)
Overall number of preferences wrongly predicted by weights (2)	25(17+8)
Overall number of preferences indicated (at other than the unsure confidence level) (2)	78(50+28)

(1) scaled so that the weights of the separate subproblems sum to one.

(2) (n+m) means that n were expressed at the "certain" level of confidence, and m were expressed at the "reasonably sure" level of confidence.

These data are quite similar to those of Tables III, IV, and V and much of the earlier discussion continues to apply here. The slightly better predictive performance in the mid-range levels of the attributes is not considered significant.

4.2.2 STAGE 2 RESULTS

The second stage results are reported in Table XI. These data were scaled so as to have the variables sum to 30 for the simple expedient of improved visual assessment. The differences between the values in Table XI and Table VI are considered slight and are discussed below.

The numerical value assigned to y_{215} at the second stage is positive instead of zero. Although this is the desired result, the result does not negate the discussion in an earlier section regarding the social structure attribute. The fact remains that the DM considered the attribute important and it should be explicitly included in the model. A possible reason for the nonzero value is that with confidence coefficients of 1 and 1, the "certain" responses, and hence the preferences due to the requirement considerations, are weighted less than they are with confidence coefficients of 2 and 1. Therefore requirement violations which result in mismatches tend to remain hidden because they do not influence the determination of the numerical weights any more than the "reasonably sure" responses do. This observation may also explain the second significant difference in results.

This second significant difference for the derived scores is that the model does not predict overall preferences any better when only "certain" subcomponents of score are used to obtain the overall score. This may likely be due to the fact that since the overall perferences expressed by the DM were often influenced heavily by violated requirements, the model with confidence coefficients of 2 and 1 predicts overall preferences better using "certain" subcomponents since it "weighs" the preferences due to requirement consideration more when determining the weights. The model with confidence coefficients of 2 and 1 does not.

Table XI

Second stage results with confidence coefficients of 1 and 1 and d = .00124

Noise

Unknown variables	y_{111}	y_{121}	y_{131}	y_{211}	y_{222}	y_{231}
Numerical Weights	.0	.0	.0	.02841	.0	.0
Scales Weights	.0	.0	.0	.26984	.0	.0

Temperature

Unknown variables	y_{112}	y_{122}	y_{132}	y_{212}	y_{222}	y_{232}
Numerical weights	.03343	.0	.0	.04539	.00495	.0
Scaled weights	.31748	.0	.0	.43112	.43112	.0

Humidity

Unknown variables	y_{113}	y_{123}	y_{213}	y_{223}
Numerical weights	.0	.00225	.00187	2.63527
Scaled weights	.0	.02135	.01779	25.01844

Nearness to desired deck

Unknown variables	y_{114}	y_{214}
Numerical weights	.0	.34606
Scaled weights	.0	3.28659

Functional Performance

Unknown variables	y_{115}	y_{215}	y_{315}
Numerical weights	.0	.00899	.05317
Scaled weights	.0	.08540	.50494

Objective function value	.54
Index of fit, C	.01
Overall number of preferences correctly predicted by weights (2)	69(44+25)
Overall number of preferences wrongly predicted by weights (2)	18(11+7)
Overall number of preferences indicated (at other than the unsure confidence level) (2)	87(55+32)

(1) scaled so that the weights sum to 30

(2) (n+m) means that n were expressed at the "certain" level of confidence, and m were expressed at the "reasonably sure" level of confidence.

5.0 LAYOUT SCORES

In the questionnaire administered to the DM, he had been asked to indicate his preferences in the matrix which is represented in Block form in Figure II.

	Individual Attribues	All Attributes
Individual Activities	A	B
Entire Layout	C	D

Figure II. Block Diagram of Preference Responses

The responses in Block A, corresponding to individual activities and individual attributes, were used to obtain the values of the variables of the first stage of the model. The reponses in Block B, corresponding to individual activities and all attributes considered simultaneously, were used to obtain the values of the variables of the second stage of the model.

Using the weights obtained in the two stages, it is possible, according to the proposed additive model, to predict the preferences of DM for entire layouts. The DM had been asked at the first session to indicate his preferences for layouts considering each attribute separately (Block C) followed by considering all the attributes simultaneously (Block D). An attempt was therefore made to see if the preferences predicted by the model for Blocks C and D matched the preferences indicated by the DM.

The DM's responses for the cases when he was not unsure of his responses, and the predictions of the model are indicated in Table XII where the confidence coefficients were 2 and 1. The predictions of the model for Block C (considering each attribute separately) were the same, irrespective of whether the weights corresponding to d=.00124, d=.05, or d=.25 were used. This indicates, from the limited sensitivity test, that the predictive power of the model is quite insensitive to the choice of d. Considering all the attributes simultaneously (Block D), the results with d=.25 predicted one extra pairwise comparison correctly, which the others did not. Hence this set of weights was used for the predictions in Table XII.

Note that the predictions and scores considering all the defined attributes simultaneously (Block D) are dependent on the predictions and scores considering the attributes separately (Block C). Hence when considering the number of correctly and wrongly predicted preferences, one should ideally not combine the results of Blocks C and D.

The validation of this stage of the model was made difficult because of the missing input on flow attributes, due to the DM incorporating social requirements in his responses. Although location restrictions due to social structures were considered by the DM when expressing some preferences, these considerations were not originally delineated. Thus, some of these considerations constituted requirements of a constraining type discussed earlier, and these constraints were violated by the proposed layout designs.

Table XII

Comparison of actual preferences for the entire layout versus predicted preferences using confidence coefficients of 2 and 1.

Block C

Attribute	Layout Pair (1)	Confidence Level (2)	Layout preferred by DM	Prediction of model (3)	Prediction of model considering "certain" subscores (4)
Noise	AB	1	B	-1	-1
	BC	1	C	1	1
	CD	1	C	1	1
	AC	1	C	1	1
	AD	1	D	-1	-1
	BD	2	D	1	1
Temperature	CD	1	D	1	1
	AD	1	D	-1	1
	BD	1	D	1	1
Humidity	CD	1	D	-1	1
	AD	1	D	-1	—
	BD	1	D	-1	—

Functional Performance	AB	2	B	-1	-1
	BC	2	C	1	1
	AC	1	C	1	1
	AD	1	D	1	1
	BD	2	D	1	1
	Block D				
Attributes considered simul- taneously	AB	1	C	1	1
	AB	1	C	-1	-1
	AD	1	D	-1	-1
	BD	1	D	1	1

Number of correct and wrong predictions considering attributes simultaneously (Block D)	+ 2, -2	+ 2, -2
Number of correct and wrong predictions considering attributes separately (Block C)	+ 10, -7	+ 12, - 3

(1) A, B, C, D were four layouts used for pairwise comparisons

(2) 1: certain 2: reasonably sure

(3) 1: correct prediction -1: wrong prediction

(4) same as (3). —— indicates prediction was not possible

Consequently there were layouts considered to be very good in most respects, but they were rejected based on certain unsatisfied requirements.

Some requirements, other than those related to the social attribute, were also uncovered when the DM was asked to give the reasoning behind certain choices that were made. For example the DM considered it very undesirable to have the machinery area near the freezer area because of temperature effects. It was extremely undesirable to have the engine room below the medical wardroom (the situation was encountered in Layout A) because of the noise generated by the engine room.

Were Layout A not penalized so much by the DM on basis of the one violated requirement, the performance of the model would have improved so that out of the seven wrongly predicted preferences in Block C, five could have been correctly predicted, resulting in a net score of 15 correct predictions and 2 incorrect. Similarly in Block D. all four preferences could have been correctly predicted. It should be noted that this is merely speculation since other requirements were also involved. The important point is that such requirement violation problems should not exist in layouts used for comparison judgments. Such instances represent cases where the DM is uncompromising. The model is however concerned with obtaining weights for evaluation where such rigid standards have been met, and a choice must be made considering the attributes, and the trade-offs and compromises that the DM is willing to make among them.

In an attempt to focus on the requirement aspects in order to make predictions (something that the model was not originally designed to do), scores were computed once again for Block C by considering only those subcomponents of total scores where the DM had made a preference judgment in Block A at the "certain" level of confidence when he was comparing layouts with respect to individual activities and attributes. The assumption here is that if any requirement was violated, the DM was likely to be "certain" of his choice. Thus if the DM indicated that he preferred Layout A over Layout B at the "certain" confidence level when considering activity 2 with respect to the noise attribute, then the score of activity 2 with respect to noise would be considered when predicting the choice between Layouts A and B. If the confidence level was any less than "certain" this part of the score would not be considered.

Predictions made on this assumption resulted in a much better predictive capability of the model for Block C. There were 12 correct predictions and 3 wrong ones. Two predictions could not be made because of intransitivities. These intransitivities may be expected because subcomponents of score may be considered in one instance and not in others. As an example, consider the case where by using the subcomponents of the score, Layout A is preferred overall to Layout B which is preferred to Layout C. But Layout A could be predicted to be indifferent with respect to Layout C if all preferences between A and C were at less than "certain" levels of confidence.

In general, the results using confidence coefficients of 1 and 1 as presented in Table XIII are very similar to the results using confidence coefficients of 2 and 1. The numerical values of the variables, and the number of correctly and wrongly predicted preferences are almost the same in the corresponding pairs of tables.

Table XIII

Comparison of actual preferences for the entire layout versus predicted preferences using confidence coefficients of 1 and 1

Block C

Attribute	Layout Pair (1)	Confidence Level (2)	Layout preferred by DM	Prediction of model (3)	Prediction of model considering "certain" subscores (3)
Noise	AB	1	B	-1	-1
	BC	1	C	1	1
	CD	1	C	1	1
	AC	1	C	1	1
	AD	1	D	-1	-1
	BD	2	D	1	1
Temperature	CD	1	D	1	1
	AD	1	D	-1	-1
	BD	1	D	1	1
Humidity	CD	1	D	-1	-1
	AD	1	D	-1	-1
	BD	1	D	-1	-1

Functional	AB	2	B	-1	-1
	BC	2	C	1	1
	AC	1	C	1	1
	AD	1	D	1	1
	BD	2	D	1	1
			Block D (equation (5.9))		
Attributes considered simul- taneously	BC	1	C	1	1
	AC	1	C	-1	-1
	AD	1	D	-1	-1
	BD	1	D	1	1

Number of correct and wrong predictions considering attributes simultaneously (Block D)	+ 2, - 2	+ 2, - 2
Number of correct and wrong predictions considering attributes separately (Block C)	+ 10, - 7	+10, - 7

(1) A, B, C, D were four layouts used for pairwise comparisons

(2) 1: certain 2: reasonably sure

(3) 1: correct prediction -1: wrong prediction

6.0 CONCLUSIONS

Detailed conclusions have been stated in various sections of this report and various problem areas have been highlighted. The summary conclusion that can be drawn is that the model does seem to give encouraging results although it has not yet undergone sufficient validation testing.

One key step toward further validation is that of improving the questionnaire interface with the DM. The "hard copy" questionnaire [1] is simply too cumbersome with volunteer surrogate decision-makers. Toward such an improvement, the consideration of an interactive computer-based data development system seems especially promising, particularly when coupled with graphics displays at the user terminal.

7.0 REFERENCES

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