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# HEURISTIC SOLUTION METHODS FOR MULTI-RESOURCE 

GENERALIZED ASSIGNMENT PROBLEMS

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Thesis Approved:


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This dissertation could not have been written without the contributions of a whole series of people. The most direct contributions were made by my wife, Nina, and by Kenneth E. Case, the chairman of my advisory committee.

Nina took in sewing in a cramped apartment where the temperature was twenty degrees warmer than any she had ever experienced. In spite of her unfamiliarity with American bureaucrats, banks, and automobile mechanics, she ran nearly all the errands that otherwise would have stolen a great deal of time from learning and research. Her imagination and creativity with limited resources made our apartments cozy places to work. Unlike most of her contemporaries, she had to leave her homeland and family six years ago, knowing that we could not afford even a short visit during the time $I$ was a student. She expressed her love and confidence in many other ways that encouraged me when $I$ needed it most.

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Mrs. Linda Howard took the hideous job of typing this dissertation at the last minute, worked around my disorganized schedule, and used her experience and wisdom to make a cohesive whole out of a pile of messy papers. .

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## CHAPTER I

PROBLEM SUMMARY AND RESEARCH OBJECTIVES

## Introduction

The objective of this dissertation is to develop and evaluate heuristic solution methods for multi-resource generalized assignment models, including some variations and complications. These problems belong to a class for which efficient optimal solutions probably cannot be developed. Without using references or symbols, this chapter summarizes the problem, justifies and develops the approaches and objectives of the research, and reports briefly the results that have been obtained and the contributions that have been made.

## Problem Summary

## General

A11 assignment models are similar in seeking the best assignments of a set of "agents" to a set of "tasks." Typical applications are assigning machines or workers to jobs, factories to production orders, merchandise types to warehouse spaces, deployment of medical resources in catastrophic situations ("triage"), and many others. For example, the original motivation for this research was assignment of artillery to military targets.

## Previous Approaches

In the "classical" assignment problem, the number of agents and taks is, perhaps after a simple augmentation, the same. Each agent is assigned to exactly one task as some objective function is optimized. The "generalized" assignment model allows the assignment of several tasks (or none at all) to each agent, so long as the tasks do not exceed the agent's capacity of some resource.

## Multi-Resource Models

The primary concern of this research is the extension of generalized assignment models to consider several resources for each agent. The need for this is illustrated by an example in Chapter II, where an elegant solution of a single-resource model is (invalidly) used for a multiresource problem.

Complications and Reality

Secondary consideration is given to some of the complications that arise in actual problem situations. These include variations on the model, such as:

Scheduling the execution of the assignments, including prior restrictions on the schedule.

Incorporating discretionary resources for some agents; that is, a decision must be made as to which category of a given type of resource would be used for a given task.

Allowing mixed assignments, in which agents can share some tasks.

Task distribution leveling, an attempt to avoid solutions where very efficient agents may be overloaded, while others are idle or nearly so, even though no constraints are violated.

Combinations of some or all of the above variations.

Other complications arise in the problem-solving environment:
Limited computer resources may be all that are available.
Conversational response times are often required.
Simplicity of use is very important.

Summary and Justification of Solution Approaches

## Optimal Approaches

There is probably no hope of obtaining a nonenumerative optimal solution to a multi-resource problem of realistic size, where the number of agents times the number of tasks may be well over a thousand. Branch-and-bound logic has always been the most efficient enumerative way to attack this kind of problem. For some single-resource problems this has been fairly satisfactory, approaching conversational speed, but the problems lacked variations. Also, the fastest results were associated with problems where the number of agents was very small compared to the number of tasks. This combined in fortunate coincidence with the single-resource characteristic to allow especially rapid solution. Current computer technology will probably not allow optimal solution of multi-resource problems in conversational time, especially if complications are present.

## Heuristic Approaches

This dissertation describes and evaluates heuristic solution methods. Certain characteristics of multi-resource problems bear on the development of these methods.

Un1ike classical assignment or transportation problems, these problems cannot readily be checked for possession of a feasible solution
(i.e., one covering all tasks). It is probably just as difficult to devise a procedure that can always detect a feasible solution (if one exists) as it is to develop an optimal algorithm. For this reason, the best any heuristic procedure can do is to frequently find an excellent feasible solution. Also, the only way of testing any solution for optimality consitutes an optimal solution method for the entire problem. Further, without re-solving the problem from the beginning, it is a matter of guesswork to determine how resource limitations should be changed in order to improve a solution or perform sensitivity analysis.

## Justifying the Heuristic Approach

Why, then, is it desirable to develop heuristic approaches at all? This is answered by examining justifications for use of heuristic methods (1) in general, and (2) with this class of problems.

## Solution Time and Its Variability

One justification has already been mentioned: solution time. Up to this point, however, only the duration itself was emphasized, and not its variability. In management planning or systems design, it is helpful to be able to predict response time. Heuristic methods can frequently be designed to require a fixed (or bounded) amount of time (thus enabling the use of worst-case analysis), but a branch-and-bound algorithm's time usage can vary through a vast range. This variability also applies to storage requirements.

## General Usefulness

Heuristics are useful in spite of the aforementioned difficulty in finding a feasible solution. The fact is that in actual practice,
many feasible solutions usually exist, so a good one will be obtained by a well-designed heuristic. Management will usually be willing to allot additional resources or reduce the number of tasks if a normally reliable method has failed to find a feasible solution. Sometimes it is sufficient to minimize the number of unassigned tasks, as in triage. Also, several different heuristics can be used on a problem. Perhaps one will find an answer where others do not.

## Multiple Alternatives

Heuristics can be designed to provide several attractive solutions, from which the most suitable can be chosen according to secondary objective requirements that may be impossible to codify. This is not true of most optimal procedures.

## Inexact Data

Data are almost always so inexact that a good approximate solution cannot be called inferior to a solution obtained by optimal methods. Also, the difference between optimal and approximate objective values will often be less than the incremental cost of the optimal solution.

Flexibility

Heuristics are typically far more adaptable to changing requirements than are optimal methods. The former are not required to be as precisely formulated (in a mathematical sense) as are the latter. Indeed, as will be seen, some of the more successful methods developed by this research descend directly from heuristics developed for quite different problems. Although branch-and-bound methods are relatively
easy to adapt compared to other optimal methods, they do not approach the flexibility of heuristic methods.

Improving Optimal Methods

Branch-and-bound methods themselves provide two other justifications for heuristic solution methods. A very good bound on the optimal solution can be obtained, thus enabling early elimination of large numbers of nodes. Also, the branching process uses heuristic rules to find promising branches.

## Choosing Heuristic Approaches

Whatever the justification for use of heuristic methods, it must eventually be decided which of the literally infinite number of possible approaches to take. This is, of course, determined to some extent by the design objectives and performance standards that will be specified. One cannot, however, escape the fact that designing a heuristic is an intuitive process in which inspiration comes from experience and investigation of the work of others.

## Construction Heuristics

The first heuristic approaches that will be described here are those that construct a solution. Most of them attempt to progressively augment a partial solution by adding an especially attractive agent-task combination. This process is guided by some intuitively developed intermediate logic that seeks a better solution than would be achieved by simply assigning successive tasks to the cheapest available agent. The intermediate logic is where experimentation has been done. The approaches of this research include:

Random intermediate logic, where many complete solutions are generated at random.

Penalty methods, quite similar to Vogel's approximation method.
"LP-guided" methods, where successive assignments are based on variable values in a linear programming solution.

## Improvement Heuristics

Additionally, ways have been developed to improve an existing solution. Two strategies try to obtain a savings by switching the assignment of two tasks to different agents:
"Greedy" methods, which make the first profitable switch found.

CRAFT-type methods, motivated by the well-known layout procedure, which make the most profitable switch found after examining all possibilities.

## Objectives

Development

Specific design objectives come from analysis in which desirable performance characteristics are determined by (a) the requirements and limitations derived from the operating environment, and (b) cost-effectiveness versus other possible approaches.

## Requirements and Limitations

The most important requirements involve:
The problem definition in terms of size and complexity. The size of a realistic problem (in tasks times agents) can vary from about ten to thousands. Many applications deal with multiple resources, and complicating variations may be present.

Response time, measured in real elapsed time. This requirement may vary considerably. It might be a few minutes in emergency or wartime situations, or "on-the-spot" in a factory. An hour or two would satisfy most managers. Problems involving large, long-term investments could justify much slower response, if a solution could be sufficiently improved or shown to be nearly optimal. This leads to the next type of requirement.

Accuracy, in terms of nearness to the optimum solution (if one exists and can be found, or if a reasonable set of bounds can be determined). As has been mentioned, problem data are usually inaccurate. However, for the previously mentioned investment situation, or for a procedure that will be used many times, there may be reason to strive for high accuracy. Very good data will be needed, though, if the added effort is to be costeffective.

Feasibility, or coverage of all tasks. This can be the most important requirement. As has been noted, however, there is probably no way to be sure of finding a feasible solution, and it is equally difficult to determine what should be done to introduce feasibility. Since feasibility is so important, it is necessary to detect when (a) it is certain that no feasible solution exists, and (b) it is probable that none exists. Heuristic rules for slack analysis can help guide the relaxation of constraints.

Limitations, besides those noted in conjunction with data accuracy,
arise from the resources available for implementation:
Personnel resources are limiting in that any solution method is more useful if it is as simple as possible to implement, maintain, use, and modify.

Computer resources can be limited in speed, storage, peripheral devices, and programming languages. Many of the methods described are compatible with some of the smallest microcomputers.

## Cost-Effectiveness

Note that the requirements of response time, accuracy, and feasibility bear directly on cost-effectiveness. There must, however, be some basis for comparison. What would a user do if this research had not been undertaken? The incremental improvement would have to be measured against the incremental cost.

No reasonable alternative is known to be available. It is estimated that the best optimal branch-and-bound algorithm that could be developed for a typical multi-resource problem with two resources, 15 agents, and 100 tasks, with no complicating variations, would have a response time of about thirty minutes and would require about a million bits of storage, using existing computer technology. The storage requirement is reasonable only for fairly large computers, and the response time would be suitable for only a few applications.

Based on the above paragraphs and earlier discussion, three points can be made about the cost-effectiveness of this research:
(1) There is apparently no other way to obtain a solution quickly enough. This means that the limiting value of the method is the value of the solution, for which users are willing to bear development costs of five to seven digits.
(2) The incremental cost of a single heuristic problem solution is at most a few dollars.
(3) Refinements to approach optimality should be made only if the improvement is of greater value than the cost of the refinement. No refinement is justified that produces a solution closer to the optimum than the amount of error in the data, which is usually very difficult to measure.

## Objectives

The objectives given below are based on the requirements and limitations encountered in the assignment of air and artillery units to military targets. This is the application where the most taxing requirements occur ("worst case" philosophy), and actual problems are available. Many complications are present, response times on the order of five minutes are desired, multiple daily use places some premium on accuracy (although data are often estimated), problems are frequently so highly
constrained that feasibility is the most important consideration, and personnel will usually be familiar only with input-output characteristics. The computer, for which specifications are currently sketchy, will use fairly recent technology. Total storage will probably be limited to 500,000 bits. (As was noted, methods suitable for microcomputers are also included).

The precise objectives of this research can now be stated: To devise heuristic solution methods substantially fulfilling the aspiration levels given below for realistic multi-resource generalized assignment problems. A realistic problem is defined as one whose size (tasks times agents) is on the order of ten to a thousand, possibly including one or more variations. Primary emphasis is placed on the multiple-resource model without variations. This model contains the features believed to be common to most applications, thus warranting the most thorough investigation. Variations may or may not apply to specific problems. Those that apply may be present in widely varying forms and severities. Therefore, procedures for handling variations are demonstrated to the extent that they have been identified in actual problems and dealt with to the user's satisfaction. It is emphasized that procedures for solving the basic multiple-resource problem have been planned for adaptability to variations encountered in practice. Suggestions are made for dealing with the variations.

## Aspiration Levels

The first category of secondary objectives is evaluation of the methods that have been developed according to the following aspiration levels and qualitative criteria:

Coverage (feasibility): A single aspiration level cannot be set. For problems appearing to be fairly loosely constrained, it is not unreasonable to hope that solutions covering all tasks would be found in at least 90 percent of the cases tested (some of which, despite appearances, probably do not possess feasible solutions). The deterioration of this performance becomes more severe as constraints tighten, since more problems are probably actually infeasible.

Response time: A reliable response time on the order of five minutes is the aspiration level.

Accuracy/Optimality: The aspiration level for this factor is to produce a solution within 15 percent of the optimum in 90 percent of the cases where a feasible solution is found and the optimum is known or can be adequately bounded.

Computer Storage: The aspiration level is to use an amount of storage (bits) that does not exceed 300 times the product of the numbers of resources, agents, and tasks.

Other: Qualitative evaluation criteria include:
(a) Adaptability to introduction of variations, which is necessary for any method to be of general applicability.
(b) Availability of multiple solution alternatives subject to virtually instant access, which would be highly desirable in order to better satisfy additional secondary or transient objective criteria.
(c) Ease of implementation, operation, and maintenance, which would be critical to actual usefulness.
(d) Predictability of response time.

## Evaluation Techniques

Another category of secondary objectives is to determine whether the above criteria have been satisfied. It is not intended to evade the usual research technique of evaluating an approximation by comparing it to the value being approximated, but the ill-conditioned nature of this class of problems makes it impractical to obtain exact information
about optimality and feasibility. Therefore, the following techniques are used to overcome these difficulties:

Special heuristics enable probabilities to be calculated for obtaining a solution within a certain quantile of all solutions.

Continuous methods (linear programming) give additional information about existence and bounds of solutions.

Tests on smaller problems give some intuitive support while enabling more thorough use of special heuristics and continuous methods.

## Summary of Results

Where measurements were possible, objectives were usually satisfied beyond the aspiration levels by one or more methods. This section summarizes the results for each category of objectives.

Realistic Problems: A method was developed that will be used by the U. S. Marine Corps in a conversational implementation to solve artillery problems containing every variation that has been described. It is described in Chapter V. Elsewhere in Chapter V, some ways are suggested for considering variations in basic methods, even when the methods are implemented on a microcomputer.

Coverage: A solution covering all tasks was always found unless known not to exist. If no solution existed, about 90 percent confidence could be associated with covering as many tasks as possible.

Response Time: Response times under five minutes could be guaranteed with the best methods on most computers.

Accuracy/Optimality: Ninety-four percent of the answers were within 15 percent of the optimum, under stricter conditions than aspired to. Results support very high confidence of obtaining a solution superior to all but a few other solutions.

Computer Storage: Depending on the output and user options desired, storage requirements were well within the aspiration level. Also, special methods for saving storage are discussed in Chapter $V$.

Evaluation Techniques: Basic methods, either modified or used in slightly different ways, gave most of the information needed.

## Contributions

General

This research has made several contributions. Besides the solution methods themselves, these include problem definition, evaluation methodology, and realistic applications.

Heuristic Methods

Considerable effort and inspiration were necessary to combine methods used with other classes of problems. Powerful heuristics were produced by adapting such methods to the characteristics of multiresource generalized assignment problems.

## Problem Definition

Although these problems are frequently encountered, no discussion of their multi-resource aspect was found in the literature. Researchers have used algorithms that are "optimal" for single-resource problems. Such an approach is itself heuristic. This dissertation establishes the need to consider multiple resources explicitly.

Evaluation Methodology

It was necessary to develop most of the evaluation methodology. The literature is weak in describing evaluation methodology for heuristics in general. Therefore, this dissertation may well serve as one of the more comprehensive sources of ideas for evaluating any heuristic.

## Realistic Applications

```
Researchers confronted with actual problems will seldom find preexisting solution methods that can be applied unchanged. This dissertation describes the adaptation of some of its heuristics to fit specific applicational requirements, thus serving as a possible source of inspiration.
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## CHAPTER II

THE PROBLEM IN LITERATURE AND PRACTICE

## Introduction

The classical assignment model occurs in almost every textbook (see [17, 31 and 33]). Agents and tasks are interchangeable because of the assumption that each agent has enough resources for exactly one task. Ross and Soland [26] point out that a model would be more useful if it allowed the assignment of several tasks to a single agent, so long as these tasks do not use more of some resources than the agent has available. However, they and others [3, 4, 9 and 29] did not go beyond one resource. This chapter presents mathematical models and discusses applications, beginning with the single-resource problem, but primary emphasis is placed on the extension to multiple resources, with additional discussion of problems with variations.

```
Single-Resource Problems
```


## Models

Figure 1 is a model of the single-resource problem. It was adapted from Ross and Soland [26], to whom the terms "agent," "task," and "generalized assignment problem" are also due. A similar model is given by Balachandran [3, 4].

Minimize $\sum_{i=1}^{m} \sum_{j=1}^{n} c_{i j} x_{i j}$

Subject to:

$$
\begin{array}{ll}
\sum_{j=1}^{n} a_{i j} x_{i j} \leq b_{i} & i=(1,2, \ldots, m) \\
\sum_{i=1}^{m} x_{i j}=1 & j=(1,2, \ldots, n) \\
x_{i j}=0 \text { or } 1 &
\end{array}
$$

where

$$
\begin{aligned}
m & =\text { number of agents } \\
n & =\text { number of tasks } \\
c_{i j} & =\text { cost incurred if agent } i \text { is assigned to task } j \\
a_{i j} & =\text { resource required by agent } i \text { to do task } j \\
b_{i} & =\text { amount of resource available to agent } i \\
x_{i j} & =1 \text { if agent } i \text { is assigned to task } j \\
x_{i j} & =0 \text { if otherwise }
\end{aligned}
$$

Figure 1. Mathematical Model of Single-Resource Generalized Assignment Problem

Figure 1 reduces to the classical assignment model if we let $a_{i j}=$ $b_{i}=1$. De Maio and Roveda [9] and Srinivasan and Thompson [29] discuss the special case that can be interpreted as a generalized transportation model where each destination must be supplied from a single source. This can be represented by allowing $a_{i j}$ to be $a_{j}$ in Figure 1.

## Applications

Many specific applications have been cited, especially in Ross and Soland [26]. They include assignment of software development tasks to programmers, assignment of jobs in computer networks (Ross and Soland [26] cite a working paper for Balachandran [3], assignment of contractual payments or television commercials to time periods, along with fixed charge plant location models (Ross and Soland [26] cite Geoffrion [13] and Gross and Pinkus [16] here) where each customer must be supplied by one plant, and communication network design models with node capacity constraints (Ross and Soland [26] cite Grigoriadis et al. [15]).

## Multi-Resource Problems

## Justification

Actually, many of the applications cited above may be multiresource situations that have been simplified in order to make them analytically tractable. For example, Balachandran [3, 4], in discussing the assignment of jobs to computers in a network, states that each job requires resources such as CPU time, memory, software, or peripherals. Later, the problem is simplified dramatically by associating an infinite cost with combinations for which the job's
requirements for one or more resources exceed the total capacity of the computer. The only constrained resource is "processing time," giving a model like Figure 1. It is not clear whether "processing time" is CPU time or elapsed time, but the multi-programming capabilities of the computers involved appear to invalidate the single-resource model in either case. This example shows why it is often necessary to consider multiple resources in generalized assignment problems. All of the models discussed below would require modification to adequately describe Balachandran's problem (which could probably be said of most applications), but the need for investigation of multi-resource problems seems well-established.

The Basic Multi-Resource Model

Figure 2 was derived from a model developed during preliminary research dealing with assignment of artillery units to engage enemy targets [6]. (Note that Figure 2 can be reduced to Figure 1 by letting the number of resources (p) be one.) In the artillery problem, two resources are involved: ammunition and time. The computer network [3, 4] problem dealt with resources of five types, most of which should have been considered explicitly, although software can be handled with Balachandran's infinite-cost approach. This technique has been used elsewhere [6, 26], and is mentioned in standard texts [17, 31, 33].

The Unconstrained Optimum

## Definition

If the resource constraints (1-2) and (2-2) are disregarded in Figures 1 and 2, an optimal solution becomes readily available by

```
    m n
Minimize
\(\sum_{i=1} \sum_{j=1} c_{i j}{ }_{i j}\)
```

Subject to:

$$
\begin{array}{ll}
\sum_{j=1}^{n} a_{i j k} x_{i j} \leq b_{i k} & \begin{array}{l}
i=(1,2, \ldots, m) ; \\
k=(1,2, \ldots, p)
\end{array} \\
\sum_{i=1}^{m} x_{i j}=1 & j=(1,2, \ldots, n) \\
x_{i j}=0 \text { or } 1 &
\end{array}
$$

where

$$
\begin{aligned}
& p=\text { number of resources, indexed by } k \\
& a_{i j k}=\text { amount of resource } k \text { required by agent } i \text { to do task } j \\
& b_{i k}=\text { amount of resource } k \text { available to agent } i \\
& \text { (Other notation is identical to that in Figure } 1 \text { ) }
\end{aligned}
$$

Figure 2. Mathematical Model of Multiple-Resource Generalized Assignment Problem
simply assigning each task to the cheapest agent. Such a solution, which has also been called the "trivial solution" [26], will be referred to in this dissertation as the "unconstrained optimum." Strictly speaking, of course, the problem has become "unconstrained" only in terms of resources. The other restrictions remain because these could otherwise no longer be called "assignment problems."

## Complicated Multi-Resource Problem

## Introduction

Despite the extended generality of the basic multi-resource model in Figure 2, it would need to be modified for most applications. Although it is neither possible nor practical to construct a model that will be of complete generality, it seems to be a worthwhile example to expand the basic model to cover several variations, especially since such an application has been identified.

The expanded mathematical model, however, is quite complex, which limits its usefulness. Therefore, this section begins with a Model Summary, followed by the model itself and a discussion of its components.

## Model Summary

The meaning of each expression in the model is given below:
(3-1) (Objective function) Minimize a weighted combination of:
(a) total cost
(b) disparity in task distribution
(c) deviation from desired mixed assignments.
(3-2a) (Ammunition constraints) No unit may use more of a particular type of ammunition than is available.

| (3-2b) | (Time constraints) Units may not exceed the specified amount of time available. |
| :---: | :---: |
| (3-3a) | (Binary coverage constraints) Targets for which mixed assignment is not desired must have exactly one unit assigned to cover them completely. |
| (3-3b) | (Mixed coverage constraints) Units in a mixed assignment must provide aggregate coverage that is sufficient for the target. |
| (3-4a) | (Mixed assignment restrictions) For a unit firing a given type of ammunition at a given target in a mixed assignment: <br> (a) Each gun in the unit must fire at least one shell. |
|  | (b) The unit's fractional coverage of the target is equal to the number of shells fired divided by the number the unit would need to fire to cover the whole target. <br> (c) A record must be kept of the particular combination of unit, target, and ammunition type. |
| (3-4b) | (Binary assignment restrictions) In "unmixed" assignments, a unit either covers all of a target or none of it. |

The Model

Figure 3 includes the variations for the most complicated version of the artillery problem, in which the agents are "units" and the tasks are "targets." The notation is given in Figure 4. Figure 3 does not include the scheduling variation, for which the additional constraints and notation are given in Figure 5.

## Priority

The model does not cönsider target priority, which is handled by solving a subproblem (of the form given in Figure 3) for each priority class in decreasing order of importance. Each subproblem has access

Minimize $h_{1} \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{p_{i}} c_{i j k}\left(x_{i j k}+y_{i j k}\right)+h_{2}\left(\underset{i}{\max } B_{i}-\underset{i}{\min } B_{i}\right)$

$$
\begin{equation*}
+h_{3} \sum_{j=1}^{n} c_{j}^{\prime}\left(M_{j}, M_{j}^{\prime}, G_{j}, G_{j}^{\prime}\right) \tag{3-1}
\end{equation*}
$$

Subject to:

$$
\begin{align*}
& \sum_{j=1}^{n} a_{i j k}\left(x_{i j k}+y_{i j k}\right) \leq A_{i j} \quad \begin{array}{l}
i=(1,2, \ldots, m) ; \\
k=\left(1,2, \ldots, p_{i}\right)
\end{array}  \tag{3-2a}\\
& B_{i}=\sum_{j=1}^{n} \sum_{k-1}^{p_{i}} t_{i j k}\left(x_{i j k}, y_{i j k}\right) \leq T \quad i=(1,2, \ldots, m)  \tag{3-2b}\\
& \sum_{i=1}^{m} \sum_{k=1}^{P_{i}} x_{i j k}=1 \quad j \in J_{b}  \tag{3-3a}\\
& \sum_{i=1}^{m} \sum_{k=1}^{p_{i}} y_{i j k} \geq 1 \quad j \in J_{m}  \tag{3-3b}\\
& \left.\begin{array}{l}
y_{i j k}=0 \\
z_{i j k}=0 \\
x_{i j k}=0 \\
\left.a_{i j k} y_{i j k} \in\left(0, q_{i j}, q_{i j}+1\right), \ldots\right)
\end{array}\right] \quad z_{i j k}=1 \quad q_{i} / a_{i j k}, \quad\left\{\begin{array}{l}
i=(1,2, \ldots, m) \\
j \in J_{m} \\
k=\left(1,2, \ldots, p_{i}\right)
\end{array}\right.  \tag{3-4a}\\
& \left.\begin{array}{l}
x_{i j k}=0 \text { or } 1 \\
y_{i j k}=z_{i j k}=0
\end{array}\right\} \quad\left\{\begin{array}{l}
i=(1,2, \ldots, m) \\
j \in J_{b} \\
k=\left(1,2, \ldots, p_{i}\right)
\end{array}\right. \tag{3-4b}
\end{align*}
$$

Figure 3. Mathematical Model of Artillery Problem
h Combining weight for objective function ( $\mathrm{Ch}=1$; all $\mathrm{h} \geq 0$ ).
m Number of friendly units (agents); indexed by i.
n Number of enemy targets (tasks); indexed by j .
$p_{i}$ Number of ammunition types (discretionary resources) available to unit i; indexed by $k$. (NOTE: $k$ and $p$ are used differently than in Figures 1 and 2.)
$\left.\begin{array}{l}c_{i j k} \\ a_{i j k} \\ t_{i j k}\end{array}\right\} \begin{aligned} & \text { Cost, ammunition usage, and time needed if unit } i \text { engages } \\ & \text { target } j \text { using ammunition type } k .\end{aligned}$
$x_{i j k}$ Binary assignment variable; =1 if unit i alone engages target $j$ using ammunition type $k$; $=0$ otherwise, even if unit i participates in mixed engagement of target $j$.
$y_{i j k}$ Mixed assignment variable; value is fraction of target $j$ that unit i engages using ammunition type $k$.
$B_{i}$ Total amount of time unit $i$ is firing (actually, busy).
$c^{\prime}{ }_{j}$ Cost due to deviation from mixed assignment specifications; a function of $M_{j}, M_{j}, G_{j}$, and $G_{j}^{\prime}$.
$M_{j}$ Number of units requested for mixed assignment for target $j$.
$M^{\prime}{ }_{j}$ Number of units actually assigned in mixed assignment to target j .
$G_{j}$ Set of units requested for primary consideration for mixed assignment to target $j$.
$\mathrm{G}^{\prime}{ }_{j}$ Set of units actually assigned to target $j$.
$A_{i k}$ Supply of $k$ th ammunition type at unit $i$.
T Time horizon; must be in same units as t .
$J_{b}$ Set of indices to tasks requiring binary assignment.
$J_{m}$ Set of indices to tasks requiring mixed assignment. (NOTE: $J_{b} \cup J_{m}=\{1,2, \ldots, n\} ; J_{b} \cap J_{m}=\emptyset$ ).
$q_{i}$ Number of guns located at unit i.
$z_{i j k}$ Binary indicator variable; $=1$ if $y_{i j k}>0 ;=0=y_{i j k}$ otherwise.
Figure 4. Notation for Mathematical Model of Artillery Problem
only to those resources not allocated in an earlier subproblem. This concept of absolute priority was the result of a user specification, but also occurs elsewhere, e.g., in the operating systems for IBM 360 and 370 computers. Other viewpoints exist, such as the "goal programming" approach of maximizing the number of assigned tasks as long as no tasks remain unassigned in a final solution if sufficient resources for them can be diverted from tasks of lower priority. The distinction between these two concepts of priority is rather fine--the first optimizes in groups; the second optimizes the entire problem (and would always achieve coverage at least as wide as the first). The second concept, besides being difficult to understand (which is regarded by Woolsey [34] as a fatal flaw), is computationally unwieldy and could prevent assignment of the most efficient units to the most important targets.

## Objective Function

Figure 3 incorporates only one of many possible formulations for the four objective criteria:
(1) Coverage: Maximizing the number of targets covered.
(2) Cost Minimization: Maximizing target value requires only a simple transformation.
(3) Mixed Assignments: Minimizing overall deviations from the numbers and types of units specified.
(4) Task Distribution Leveling: Minimizing the maximum disparity between any two units in fraction of available time used. Coverage is not reflected in Figure 3, because coverage can be made a consequence of cost minimization by adding to the problem a fictitious unit with unlimited resources. Any targets that could not be assigned
elsewhere could be assigned to this unit. However, the associated cost would be so great that any solution actually covering $n+1$ targets would be of lower cost than if $n$ or fewer targets were covered. This approach is also used by Balachandran [3, 4]. The objective function has been formulated as a simple linear combination of the other three criteria. Balachandran [3, 4] justifies this by noting that (a) various theoretical appraoches [12, 24, 27] would not be economically feasible because of the computation time required, and (b) the linear combination is adequate if management can assign utilities for use as combining weights. Woolsey [34] describes a procedure for obtaining and refining such weights through interaction with the user. In summary, there is little evidence that a more elaborate formulation would better represent the largely intuitive decision standard that a user would employ. It is quite possible that a heuristic will obtain an answer that will satisfy a model without operating explicitly on the model's specifications. This is true in the case of the decision variables of Figure 3, which the heuristic considers only indirectly. Also, the user has not yet decided on the final form of all objective criteria, which may portend changes in the final heuristic even though the model does not change.

## Mixed Assignments and Discretionary Resources

The model in Figure 3 also contains nonbinary variables ( $y_{i j k}$ ) to reflect the mixed assignment variation. For those targets defined by the user as requiring simultaneous engagement by more than one unit, $y_{i j k}$ represents the "fraction" of target $j$ that unit $i$ will cover using ammunition type $k$ (the use of different ammunition types is the
discretionary resource variation). The restrictions of $y_{i j k}$ and $a_{i j k} y_{i j k}$ to the sets of discrete values defined in Figure 3 (3-4a) are derived from a further requirement ("one-volley-minimum") that each participating unit must fire at least one round from each gun, with the total number of rounds fired by each unit being, of course, an integer. Note that the indicator variable $z_{i j k}$ is a count of the number of units participating in a mixed assignment on target $j$.

## Correspondence Between Models

To help understand the correspondence between models, Figures 1,2 and 3 have had their components numbered according to equivalent function. For example, (1-1), (2-1), and (3-1) are the objective functions; $(1-2),(2-2),(3-2 a)$ and $(3-2 b)$ are resource constraints; (1-3), (2-3), (3-3a), and (3-3b) are complete coverage constraints.

## Scheduling

The additional constraints and notation for the scheduling variation are given in Figure 5. The meaning of each constraint is given below:
(5-1) The duration of an assignment must be at least as great as the time required to execute it.
(5-2) An assignment to a target with a specified "start time" must be scheduled with an allowance for set-up time.
(5-3) A specified "end time" becomes the actual end time.
(5-4) If (a) only the "end time" or (b) only the "start time" is specified, the assignment must (a) start as late as possible, or (b) end as early as possible.

$$
\begin{align*}
& e_{i j}-s_{i j} \geq t_{i j k}\left(x_{i j k}, y_{i j k}\right)  \tag{5-1}\\
& s_{i j}=S_{j}-u_{i} \quad j \in J_{s}  \tag{5-2}\\
& e_{i j}=E_{j} \quad j \in J_{e}  \tag{5-3}\\
& s_{i j} \leq E_{j}-t_{i j k}\left(x_{i j k}, y_{i j k}\right) \quad j \notin J_{s} ; j \in J_{e}  \tag{5-4a}\\
& e_{i j} \geq s_{j}+t_{i j k}\left(x_{i j k}, y_{i j k}\right) \quad j \in J_{s} ; j \notin J_{e}  \tag{5-4b}\\
& \left.\begin{array}{l}
s_{i j} \geq 0 \\
e_{i j} \leq T \\
D_{i j_{1}} \cap D_{i_{j}}=\emptyset ; j_{1} \neq j_{2}
\end{array}\right\} \quad j=(1,2, \ldots, n)  \tag{5-5}\\
& \text { NOTE: In (5-1) through (5-7), } i=(1,2, \ldots, m) \\
& \left.\begin{array}{l}
s_{i_{1} j}-u_{i_{1}}=s_{i_{2} j}-u_{i_{2}} \\
e_{i_{1} j}=e_{i_{2} j}
\end{array}\right\} j \in J_{m} ; i_{1} \neq i_{2} ; z_{i j}=1
\end{align*}
$$

where

$$
\begin{aligned}
S_{j} & =\text { specified "start time" (first sheil falls on target } j \text { ). } \\
E_{j}= & \text { specified "end time" (last shell falls on target } j \text { ). } \\
J_{s}= & \text { set of targets for which "start times" are specified. } \\
J_{e}= & \text { set of targets for which end times are specified. } \\
u_{i}= & \text { set-up time for unit } i .\left(\underline{N O T E: ~} t_{i j k} \text { includes } u_{i}\right. \text { ) } \\
s_{i j}= & \text { scheduled time for unit } i \text { to begin setting up to fire on } \\
& \text { target } j . \\
e_{i j}= & \text { scheduled end of unit } i^{\prime} s \text { engagement of target } j . \\
D_{i j}= & \text { interval from } s_{i j} \text { to } e_{i j} .
\end{aligned}
$$

Other notation is as in Figures 3 and 4.
Figure 5. Additional Constraints and Notation for Scheduling Variation in Artillery Problem

| (5-5), (5-6) | Assignments must occur within the specified <br> time horizon. |
| :---: | :--- |
| $(5-7) \quad$Assignments for a given unit may not <br> overlap. |  |
| (5-8), (5-9)In a mixed assignment on a given target, <br> shells from all participating units must <br> start and stop falling on the target <br> simultaneously. |  |

These constraints come from user specifications. A problem from a different area might use entirely different scheduling constraints.

The complexity of the problem modeled in Figure 5 can be appreciated by imagining an exercise in project management where the network cannot be constructed in advance except for fragments derived from specified start and end times for some activities. Durations, costs, and materials requirements are not initially known, because it is not known who will execute each activity. Some of the usual flexibility has been removed by prior restrictions on activities that may or may not be on the critical path. Thus, the scheduling variations make the problem very difficult indeed.

Difficulty of Optimal Solution

## General

As was stated in Chapter I, generalized assignment problems are known [28] to belong to a class (called "P-complete") of problems for which it is believed that no nonenumerative optimal solutions can be obtained. The artillery problem is doubly complicated. If we regard the units as "jobs" to be scheduled for processing on "machines" representing targets, it can be seen to be an extension (mixed assignments, schedule restrictions) of the jobshop problem, which is also
known [11] to be an unpromising ("NP-complete") problem. Indeed, all problems that are NP-complete are also P-complete, but the converse does not necessarily hold [28].
"P-complete" stands for "polynomial-complete," a term derived from a formal definition of efficiency. Garey et al. [11] defines an efficient algorithm as one for which some constant $c$ exists such that the amount of time required for a problem with $n$ variables will never be above $O\left(n^{c}\right)$. ( $O\left(n^{c}\right)$ denotes a quantity that is "on the order of $\left.n^{c} . "\right)$ Such an algorithm is said $[11,28]$ to run in "polynomial time." In other words, an efficient algorithm is one capable of being executed at worst in an amount of time on the order of a constant power of the number of variables. (This definition of efficiency appeared only recently, and thus lacks wide acceptance.) P-complete problems are believed not to be solvable in polynomial time, thus requiring enumerative solutions, for which the number of iterations is on the order of $c^{n}$, which is greater than $n^{c}$ as long as $c$ is less than $n$ and $c$ is greater than 2, so enumerative solutions can be very tedious. Even the branch-and-bound methods that have been developed for singleresource problems [3, 4, 9, 26, 29] cannot be guaranteed to examine fewer nodes than on the order of $\mathrm{m}^{\mathrm{n}}$, although the fastest algorithms [3, 4, 26] never needed excessive CPU time, for randomly generated problems of 500 to 5000 variables.

## Multi-Resource Problems

Unfortunately, the optimal methods for single-resource problems offer almost no hope of extension to multiple resources. Only the algorithm of Ross and Soland [26] appears compatible with multi-resource
problems, but response times would probably be too great for most applications. Running time should be many times that of the singleresource version, which on seven $20 \times 50$ (1000-variable) randomly generated problems used between 0.199 and 1.568 minutes of CPU time on a CDC 6600, excluding input-output and editing of the data. For multi-resource problems (using the data given by Glover et al. [14] for comparative speeds of different computers in solving transportation problems) these times could increase by thousands of times if the programs were run on a more typical computer. Storage requirements would also be very great--probably several million bits.

Attempts have been made to model single-resource problems in terms of network flows, but Balachandran [3] reported that such algorithms did not appear to be amenable to guarnateeing the binary characteristics of the variables. Ross and Soland [26] compared their algorithm to two others, one of which was a network model [19] that repeatedly exceeded a 50 -minute time limit (four of seven 500 -variable problems) on the CDC 6600.

A study by Glover et a1. [14], reveals that it is difficult to equitably compare speeds of algorithms. However, it seems clear that any optimal algorithm would be too unwieldy for most applications.

BASIC HEURISTIC METHODS

## Introduction

## History and Classification

Heuristic methods are not new. Michael's lengthy review [21] reports that heuristics were once grouped with philosophy, psychology, and logic. He says the Romans recognized heuristic approaches as early as 300 A.D., and notes that both Descartes and Leibnitz tried to develop a classification system.

Michael also attempts to classify heuristic methods, as have others [5, 18, 23]. The various classifications have little in common, which may be due to each author's concentration on methods in his own field. One idea, however, that seems to fit into all systems is the concept of "construction" and "improvement" heuristics. These terms, due to Parker [23], are practically self-explanatory. Construction heuristics attempt to generate a complete solution, usually trying to proceed toward a solution that is especially attractive according to some objective criterion. Improvement heuristics operate on preexisting complete solutions in an attempt to improve the value of the objective function.

Ubiquity
several, such as the golfer who uses an old ball on a hole with a water hazard, or the motorist selecting a route through a city based on perceived traffic conditions.

Games (Michael mentions chess) constitute a familiar area where heuristic analysis is the only practical approach. Ignizio [18] cites remarks about the ability of humans to play ticktacktoe, in which most players generate a strategy to guide them through thousands of outcomes. Although chess is vastly more complex, there exists for either of these deterministic games an optimal strategy (which may be impractical to determine). Other games are complicated by stochastic elements that add possibilities for the use of heuristics. Startling similarity to the language of academic discussion of the philosophy behind heuristic strategies can be found in discussions between tournament bridge players.

## Design Process

It seems, then, that heuristics are everywhere. Everyone has an intuitive feeling for developing and using them without being able to describe exactly what is happening. Michael [21] says that the process of developing a heuristic should be based on a study of "cognitive processes," and cites Polya [25] as recommending that the basis be experience in solving problems and watching problems be solved. A more structured philosophy is difficult to achieve. Ignizio [18] points out that the infinite number of possibilities makes it easy to criticize any one choice versus the others that were possible, and that it is probably impossible to explain the design to everyone's satisfaction. How does a painter know which brushstroke completes the canvas? These
last considerations should be kept in mind when considering the methods described and evaluated in the remainder of this dissertation.

Background and Development of Specific Methods

Sahni and Gonzalez [28] have shown that P-complete problems can be as ill-suited for heuristics as for optimal methods. They conclude that any heuristic that runs in polynomial time must occasionally produce arbitrarily bad results. Therefore, neither optimal nor near-optimal results can be guaranteed to be obtainable in a reasonable amount of time. With this in mind, several heuristics were developed for this research in the hope that some may perform well when others do not.

Figure 6 outlines the heuristic methods that were developed. Many were inspired by examples described in the literature for use with problems of similar structure, such as traditional assignment and transportation models [17, 31, 33], as well as plant layout [10, 20, 23], facilities location [10, 31], covering [18], knapsack [34], and project-scheduling [8] models.

## Construction Heuristics

The construction heuristics used here all fit a classification due to Ignizio [18]. They use "add" logic, in which all variables are initially set to zero, then selectively set to one in the hope that an acceptable complete solution will result. They differ according to the type of intermediate logic that decides which variable is "added."

Some are motivated by the popular method which makes assignments at random [8, 20, 23]. This procedure has the advantage of simplicity. In pure scheduling applications [8], it has produced significantly

## I. Construction Heuristics

A. Random Intermediate Logic

1. RANDR: Random column, random row
2. RANDC: Random column, cheapest row
B. Penalty-based (VAM) Logic (all assign cheapest row)
3. VAMC: Column from VAM on costs
4. VAMI: Same, but on resource-biased costs
C. LP-guided Logic
5. LPMAX: Random column, row of max LP variable
II. Improvement Heuristic
A. GREEDY: First profitable switch
B. CRAFTY: Most profitable switch

Figure 6. Outline of Basic Heuristic Methods
better results than more refined heuristics. McRoberts [20] has done work in determining sample size and estimating the distribution of solution values. The speed and simplicity of randomly-guided layout heuristics has also been mentioned [23]. Two heuristics of this type will be described: RANDR and RANDC. Both can be used to obtain evaluation standards, and RANDC is a very good problem-solver.

Another form of intermediate logic used in this research was motivated by the Vogel approximation method (VAM), a textbook [17, 31, 33] heuristic giving good initial solutions for transportation problems. Preliminary research [7] produced two VAM-based heuristics that gave excellent results: VAMC and VAMI.

The third type of construction heuristic (LPMAX) has been used in many integer-constrained problems. Variable values from a continuous (linear programing) solution are adjusted to integers. As often noted [17, 30, 31, 33], adjustment must be judicious, or infeasibility or unacceptable suboptimality can occur. The continuous solution can also give information about bounds and existence of the discrete optimum. Unfortunately, obtaining the continuous solution to a problem of realistic size requires much storage and time, and there is little room for discretion in adjusting the variables.

## Improvement Heuristics

Parker [2] distinguishes between "greedy" methods and the well-known CRAFT [1] technique in a class that Brockelhurst [5] calls "bivariate searches." Parker and others he cited found that (for layout problems) CRAFT gave the best objective function values, but greedy methods were faster. The adaptations used here, GREEDY and CRAFTY, run so slowly
that their usefulness is limited to evaluating other methods' performances on relatively small problems.

## Specific Methods

## Introduction

This section describes in detail each of the methods given in Figure 6. Construction heuristics are described in a brief narrative followed by a detailed outline. The same logic is used to optimize a task in RANDC, VAMC, and VAMI, so it is given in detail only for RANDC. Problem data are assumed to be given. Figure 7 explains the notation used in the outlines, some of which is repeated from Figure 2. VAMC and VAMI will be described and outlined together because VAMC is implemented as a special case of VAMI.

Improvement heuristics are flowcharted rather than outlined. The flowchart makes the logic clearer by avoiding the subscripts on subscripts that an outline would use. Only one flowchart is used because of the similarity of the logic of GREEDY and CRAFTY.

Narrative Description of RANDC

The user specifies how many solutions are to be generated ("sample size"). A solution is generated simply by "optimizing" all tasks in random order. The best solutions are printed.
"Optimizing" a task means assigning it to the cheapest agent having sufficient remaining resources. If no agent is resource-feasible, a flag is set to indicate that the task remains unassigned. The "cost" of an unassigned task is set to a value (see II.D.3.c. below) that is so

| Symbol | Method (s) Where Used; Meaning |
| :---: | :---: |
| $\mathrm{a}_{\mathrm{ijk}}$ | All; Amount of resource $k$ required by agent $i$ to do task j |
| A | RANDR; Vector for shuffling agent indices |
| $\mathrm{b}_{\mathrm{ik}}$ | All; Amount of resource $k$ originally available to agent i |
| $\mathrm{B}_{\text {ik }}$ | All; Amount of resource $k$ remaining for agent i |
| ${ }^{\text {ij }}$ | All; Cost incurred if agent $i$ is assigned to task j |
| C | All; Contribution of current assignment to objective function |
| d | RANDR, RANDC; Random number seed |
| F | VAMI; Factor to balance cost-inefficiency combination |
| H | VAMI; Vector of penalties $\left\{\mathrm{H}_{\mathrm{j}}\right\}$ |
| i, j, k | All; Indices of agents, tasks, and resources, respectively |
| I, J | A11; Indices of assignment currently being constructed |
| m | A11; Number of agents, indexed by i |
| n | All; Number of tasks, indexed by j |
| N | RANDR, RANDC; "Sample Size," or number of trial solutions to be generated |
| p | A11; Number of resources, indexed by $k$ |
| P | VAMI; Matrix of inefficiency-biased costs $\left\{\mathrm{P}_{\mathrm{ij}}\right\}$ |
| Q | VAMI; Combining weight for constructing P |
| q | VAMI; Number of values of $Q$ to use |
| S | VAMI; Matrix of resource inefficiencies $\left\{S_{i j}\right\}$ |
| T | RANDR, RANDC, LPMAX; Vector for shuffling task indices $\left\{T_{j}\right\}$ |
| Figure | Notation Used in Outlines of Construction Heuristics |


| Symbol | Method(s) Where Used; Meaning |
| :---: | :---: |
| U | A11, Count of tasks that could not be assigned |
| W | RANDC, VAMI, LPMX; Vector for seeking ith smallest element in $j$ th column of $c_{i j}$ 's (modified $x_{i j}$ 's in LPMAX) $\left\{W_{i}\right\}$ |
| $\mathrm{x}_{\mathrm{ij}}$ | All; = 1 if agent $i$ is assigned to task $j$; $=0$ otherwise |
| X | All; Assignment vector $\left\{X_{j}\right\}$ : $X_{j}=i$ means $x_{i j}=1 ; X_{j}=-1$ means task $j$ cổld not be assigned |
| z | All; Current value of objective function |
| $\mathrm{Z}_{\text {min }}$ | A11; Minimum $Z$ among complete solutions found so far |

large that maximizing the number of assigned tasks is a direct consequence of minimizing total cost.

## Outline of RANDC

I. Acquire $N$ and $d$; set $T_{j}=j$ for all $j$ and $A_{i}=i$ for all $i$.
II. Generate N solutions:
A. (Re)set $u$ and $Z$ to zero.
B. (Re) set $B_{i k}$ to $b_{i k}$ for $a l l i$ and $k$.
C. Use random numbers to shuffle $T$ (task indices).
D. For all j :

1. Set $J=T_{j}$ (i.e., pick a task at random).
2. Set $\mathrm{W}_{\mathrm{i}}=\mathrm{c}_{\mathrm{iJ}}$ for all i.
3. For all i:
a. Set $I$ to index of ith - smallest $W_{i}$.
(1) If $a_{I J k}$ exceeds $B_{I k}$ for some $k$, go to II.D.3.b.
(2) If not, subtract $a_{I J k}$ from $B_{I k}$ for all k.
(3) Set $\mathrm{C}=\mathrm{c}_{\mathrm{IJ}}$ and go to II.D.4.
b. If $i<m$, go to II.D.3.a. for next $i$.
c. If not, set $C=n \operatorname{Max}_{i, j}\left(c_{i j}\right)$; set $I=-1$; Add 1 to $u$.
4. Add $C$ to $Z$, set $X_{J}=I$.
E. Print solution if new best solution or one of first five solutions.
F. Go to II.A. until N solutions have been generated.
II.D.2., 3., and 4. constitute a procedure that will be referred to as
"Optimize task J" in describing VAMI/VAMC.

## Example Solution Using RANDC

The following example problem will also be used to illustrate VAMI, as well as being quite similar to the problem solved in the computer runs of Appendix D.

Suppose the problem is to minimize

$$
40 x_{11}+87 x_{12}+60 x_{13}+79 x_{14}+89 x_{21}+63 x_{22}+58 x_{23}+10 x_{24}
$$

subject to:

$$
\begin{array}{rlr}
61 x_{11}+16 x_{12}+72 x_{13}+43 x_{14} \leq 140 i=1, k=1 & \\
19 x_{11}+16 x_{12}+46 x_{13}+50 x_{14} \leq 150 i=1, k=2 & \begin{aligned}
\text { Corresponds } \\
\text { to (2-2) in } \\
\text { Figure } 2 .
\end{aligned} \\
48 x_{21}+28 x_{22}+49 x_{23}+67 x_{24} \leq 150 i=2, k=1 & \\
36 x_{21}+62 x_{22}+51 x_{23}+81 x_{24} \leq 130 i=2, k=2 & \\
x_{11}+x_{21} & =1 j=1 & \begin{array}{l}
\text { Corresponds } \\
\text { to (2-3) in }
\end{array} \\
x_{12}+x_{22} & =1 j=2 & \begin{array}{l}
\text { Figure 2. }
\end{array} \\
x_{13}+x_{23} & =1 j=3 & \begin{array}{l}
\text { Corresponds } \\
\text { to (2-4) in }
\end{array} \\
x_{10}+x_{24} & =1 j=4 & \text { Figure 2. }
\end{array}
$$

Note that $\mathrm{m}=2, \mathrm{n}=4$, and $\mathrm{p}=2$.
Expressing the problem data as matrices and vectors to correspond with the notation of Figure 2 gives:

|  |  | $\mathrm{j}=1$ | $\mathrm{j}=2$ | $j=3$ | $j=4$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $c_{i j}$ : | $i=1$ | 40 | 87 | 60 | 79 |  |
|  | $\mathrm{i}=2$ | 89 | 63 | 58 | 10 |  |
|  |  | $\mathrm{j}=1$ | $\mathrm{j}=2$ | $j=3$ | $j=4$ | $\mathrm{b}_{\text {ik }}$ : |
|  | $\mathrm{i}=1, \mathrm{k}=1$ | 61 | 16 | 72 | 43 | 140 |
| $\mathrm{a}_{\mathrm{ijk}}$ : | $\mathrm{i}=1, \mathrm{k}=2$ | 19 | 16 | 46 | 50 | 150 |
|  | $\mathrm{i}=2, \mathrm{k}=1$ | 48 | 28 | 49 | 67 | 150 |
|  | $\mathrm{i}=2, \mathrm{k}=2$ | 36 | 62 | 51 | 81 | 130 |

e.g., $a_{132}=46, a_{241}=67$, etc.

This example will not exactly trace the outline of RANDC. Rather, it seeks to communicate the concept of repeated optimization of tasks in random order which is the main idea of RANDC. Three solutions will be generated.

Suppose the vector T is first shuffled to give the order 4, 1, 2, 3 for optimizing the tasks. Task 4 is assigned to agent 2 (the cheapest agent) at a cost of 10 . The resource supplies for agent 2 are reduced from 150 and 130 to 83 and 49. Note that it is no longer possible to assign tasks 2 and 3 to agent 2 because they would require more of resource 2 (62 or 51) than is available (49).

Task 1 is the next to be optimized. Agent 1 is cheapest at a cost of 40 and is resource-feasible. The data matrices, annotated to show the effect of the first two assignments, are:


Circled elements are those associated with assignments that have been made; those marked with an asterisk indicate that the corresponding assignment has become infeasible because of resource limitations.

The third task to be optimized is task 2. The annotated data matrices are:
$c_{i j}: \begin{array}{llll}40 & \text { (8) } & 60 * & 79 \\ 89 & 63 & 58 * & 10\end{array}$


Note that task 3 cannot be assigned to either agent. Agent 1 would require 72 units of resource 1 and only 63 are available. A similar situation exists for agent $2^{\prime}$ 's second resource, of which 51 units are needed, but only 49 units remain.

This first solution is thus complete, with a total cost of 137 $(40+87+10)$ with one task remaining unassigned.

Suppose the second RANDC solution begins by shuffling the vector $T$ to obtain the order $1,3,4,2$ for optimizing the tasks. When task 1 is optimized by assigning it to agent 1 at a cost of 40 , not enough resources are used to interfere with any potential assignment of another task. However, after optimizing task 3 via assignment to agent 2 at a cost of 58 , the potential assignment of task 4 to agent 2 becomes infeasible:


Task 4 is next to be optimized, and only agent 1 has sufficient
resources. This assignment, at a cost of 79 , does not reduce resource supplies enough to affect any potential assignment of task 2. This is therefore made to agent 2 , which is cheapest at a cost of 63 . This gives a complete solution in which no tasks remain unassigned:

slack
$b_{i k}$ :
(61) $16 \quad 72$ (43 36
(19) $16 \quad 46$ (50)

48 (28) (49) 67
36 (62) 51

81
73
17

This, as can be seen by inspection or enumeration, is the optimum solution, with a total cost of 240 .

A third RANDC solution is generated by shuffling the elements of the vector T to obtain, for example, an order of $4,2,3,1$ for optimizing tasks:

slack
$\mathrm{b}_{\mathrm{ik}}$ :
61 (16) (72) 43
52
19 (16) (46) 50 88
$a_{i j k}:$
(48) $28 \quad 49$ (67)

35
(36) $62 \quad 51$ (81)

13

The total cost of this complete solution is only 245 , so it represents a useful alternative to the optimal solution obtained earlier.

## Narrative Description of RANDR

This heuristic generates solutions by assigning tasks in random order to randomly chosen agents. Tasks are assigned only to resourcefeasible agents, however.

Outline of RANDR

This is identical to RANDC except for II.D.2. and 3. which are replaced by the following:
II.D.2. Shuffle A (agent indices)
3. For all i:
a. Set $I=A_{i}$ (i.e., pick an agent at random).

The remainder of II.D.3. is the same as given for RANDC.

## Narrative Description of VAMI/VAMC

The logic of this heuristic can probably best be understood by tracing its development. VAMC, the first heuristic developed in this research, is essentially identical to the Vogel Approximation Method, except that penalities ("H") are calculated for columns (tasks) only, and not additionally for rows as with transportation problems. The task associated with the largest penalty is optimized. Any penalties that could have changed (by some assignment becoming infeasible) are recalculated.

VAMC often produced bad results in preliminary research. It could not avoid assignments that were especially inefficient uses of resources if the relative cost was low. VAMI attempts to overcome this by combining the cost of a prospective assignment with its resource inefficiency (which is a sort of "resource cost"--the fraction of the agent's
remaining supply of the scarcest resource). Different combinations are tried, each with more weight ( $Q$ ) on inefficiency ( $s_{i j}$ ) and less (1-Q) on cost ( $\mathrm{c}_{\mathrm{ij}}$ ).

For each value of $Q$ between zero and one, a "P-matrix" of the combined cost and inefficiency elements is built. A balancing factor (F) must first be applied to make the average inefficiency equal to the average cost, because these averages usually differ by several magnitudes. Penalties are calculated from the P-matrix.

Otherwise, VAMI is the same as VAMC. In fact, VAMI is equivalent to VAMC when $Q$ is zero, because $p_{i j}$ is then equal to $c_{i j}$ (see IV.B.2. of the following outline).

VAMI resembles (and was motivated by) the optimization of a La Grangian function, with $Q$ playing the role of a multiplier. No claim is made, however, that this resemblance justifies any expectation of nearoptimal results.

Great efforts have been made to find a way to predict the best values of Q and q . Unfortunately, only the following impressions were produced:
(1) The best results were usually obtained for small (but nonzero) values of $Q$, unless constraints were very tight.
(2) The best value for $q$ was usually between 3 and 25 , with larger values of $q$ being needed for tight constraints.

The results of these observations were incorporated into VAMI as follows:
(1) The steps taken in $Q$ (see IV.C. and D.) from 0 to 0.25 are only a third as large as those taken from 0.25 to 1 , but equal in number. Allowing for the VAMC trial ( $\mathrm{Q}=0$ ) means q must be odd.
(2) $q$ can be acquired as a user input, or as a value calculated
from the data (say, 20 times average $S_{i j}$ ), or as a constant (11 usually works well). One will be added if $q$ is even.

## Outline of VAMI/VAMC

## I. Acquire q.

II. For all $i$ and $j$ where agent $i$ is feasible for task $j:$
A. Set $S_{i j}=k^{M a x}\left(a_{i j k} \div b_{i k}\right)$.
B. Accumulate $\Sigma c_{i j}$ and $\Sigma S_{i j}$.
III. Calculate balancing factor and initialize Q:
A. Set $F=\Sigma c_{i j} \div \Sigma S_{i j}$ (Sums calculated above).
B. $\quad$ Set $Q=0$.
IV. Generate the number of solutions specified by $q$ :
A. Set $u=0$ and $Z=0$.
B. For all i:

1. (Re)set $B_{i k}$ to $B_{i k}$ for all k.
2. Set $P_{i j}=(1-Q) c_{i j}+Q \cdot F \cdot S_{i j}$ for all $j$.
C. If $Q<.25$, add $1 /(2 q-2)$ to $Q$.
D. If not, add $3 /(2 q-2)$ to $Q$.
E. Set $H_{j}=$ difference between two smallest $P_{i j}$ for all $\mathbf{j}$.
F. For all $j$ :
3. If $j \neq 1$, recalculate $H_{j}$ if possibly affected by the
previous assignment.
4. Set $J$ to index of $j$ th - largest $H_{j}$.
5. Optimize task J.
G. Print first 5 solutions and all new best solutions.
H. If $Q$ exceeds 1 , stop. If not, go to IV.A.

Example Solution Using VAMI

The same problem is used as with RANDC:

|  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $c_{i j}:$ | 40 87 60 79 <br> 89 63 58 10 |  |  |  |  |
|  |  |  |  | $b_{\text {ik }}:$ |  |
|  | 61 | 16 | 72 | 43 | 140 |
| $a_{i j k}:$ | 19 | 16 | 46 | 50 | 150 |
|  | 48 | 28 | 49 | 67 | 150 |
|  | 36 | 62 | 51 | 81 | 130 |

Before generating any solutions, a matrix $\left\{S_{i j}\right\}$ of resource inefficiencies must be calculated:

$$
\begin{array}{ccccc} 
& .44 & .11 & .51 & .31 \\
S_{i j}: & .32 & .48 & .39 & .62
\end{array}
$$

As stated in the Outline of VAMI/VAMC,

$$
S_{i j}=\operatorname{Max}_{k}^{\left(a_{i j k} \div b_{i k}\right) .}
$$

For example, the value of .44 for $S_{11}$ was obtained as follows:
$S_{11}=\operatorname{Max}\left(\frac{a_{111}}{b_{11}}, \frac{a_{112}}{b_{12}}\right)=\operatorname{Max}\left(\frac{61}{140}, \frac{19}{150}\right)=\operatorname{Max}(.44, .13)=.44$

The costs and inefficiencies are summed:
$\begin{aligned} & \sum \sum \\ & i j\end{aligned} c_{i j}=40+87+\ldots+58+10=486$
$\begin{aligned} & \sum \sum \\ & i j\end{aligned} S_{i j}=.44+.11+\ldots+.39+.62=3.18$

Their ratio is calculated to use as a balancing factor in later calculations, in which it is desirable to transform the inefficiencies so that their average magnitude will be equal to average cost:

$$
F=\frac{\sum \sum c_{i j}}{\sum \sum S_{i j}}=\frac{486}{1.18}=152.83
$$

which is rounded to 153 for convenience in this example.
In the iterative portion of VAMI, the number of solutions generated is given by $q$. $Q$ is started at zero and is increased to 1 in $q$ steps, not all of which will be given here. Every solution is guided by VAM-style penalties developed from a matrix $\left\{P_{i j}\right\}$ whose elements are functions of $Q$ and the corresponding cost and balanced inefficiency values:

$$
P_{i j}=(1-Q) c_{i j}+Q F S_{i j}
$$

Note that when $Q=0, P_{i j}=c_{i j}$ and VAMI is equivalent to VAMC (i.e., penalties are calculated from costs alone, without considering potential resource problems).

Thus, for $Q=0$, penalties will be calculated from the matrix

$P_{i j}:$| 40 | 87 | 60 | 79 |
| :--- | :--- | :--- | :--- |
| 89 | 63 | 58 | 10 |

VAMI-style penalties are calculated by subracting the smallest element in each column from the second-smallest. When this is done for the above matrix, the penalty vector $\left\{H_{j}\right\}$ is obtained:

$$
H_{j}: \quad 40 \quad 24 \quad 2 \quad 69
$$

The largest penalty is 69 , associated with task 4 , which is then optimized:

| $c_{i j}$ : | 40 | 87 | 60 | 79 |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | 89 | 63* |  |  | $\begin{aligned} & \text { slack } \\ & \mathrm{b}_{\mathrm{ik}}: \end{aligned}$ |
|  | 61 | 16 | 72 | 43 | 140 |
| $\mathrm{a}_{\mathrm{ijk}}$ : | 19 | 16 | 46 | 50 | 150 |
|  | 48 | 28* |  |  | 83 |
|  | 36 | 62* | 51* | 81 | 49 |

Penalties must be recalculated, because with only two agents in the problem, any assignment must affect either the cheapest or secondcheapest agent. There is no change in the penalty for task 1 , but the cheapest agents have become infeasible for tasks 2 and 3 . Since only one agent is still available for these two tasks, the penalty is arbitrarily calculated by subtracting the corresponding $P_{i j}$ from 99998. Task 4 is already assigned, so no penalty calculation will be made for it, which is indicated by " $* *$ " in the following vector of recalculated penalties:
$H_{j}: 499991199938$ **
The largest penalty is associated with task 3, which is assigned to agent 1. This does not consume enough resources to further affect feasibility, so recalculation will not change the penalties associated with tasks 1 and 2:

$$
\mathrm{H}_{\mathrm{j}}: 4999911 \text { ** ** }
$$

Task 2 is assigned to agent 1. This makes agent 1 infeasible for task 1, which will thus be assigned to agent 2 . This gives the same nearoptimum (total cost: 246) as the third RANDC solution.

Taking further arbitrary steps of 0.1 in $Q$ will not change the solution until $Q$ reaches 0.4 , where VAMI will not yield a feasible solution. The next example uses $Q=0.5$ to obtain a new alternative solution that is only 10 percent worse than the optimum. The resourcebiased costs are:
$\begin{array}{llll}53 & 52 & 69 \quad 63\end{array}$
$P_{i j}:$
$\begin{array}{llll}69 & 68 & 59 & 52\end{array}$

These figures were obtained from the formula given earlier. For example,

$$
P_{11}=(1-Q) c_{11}+Q F S_{11}=(.5)(40)+(.5)(153)(.44)=53
$$

The $P_{i j}$ values have been truncated to integers for convenience (this is also done in the program to allow use of integer arithmetic to improve execution speed). From them a vector of penalties is calculated:

$$
\begin{array}{lllll}
H_{j}: & 16 & 16 & 10 & 11
\end{array}
$$

There is a tie for the largest penalty between tasks 1 and 2. Such ties are arbitrarily broken in favor of the lower-numbered task, so task 1 is assigned to agent 1 , because $\mathrm{P}_{11}$ is less than $\mathrm{P}_{21}$. This does not affect any potential assignment of another task, so the recalculated penalties show no change:

$$
H_{j}: \quad * * \quad 16 \quad 10 \quad 11
$$

This means that task 2 is the next to be assigned. It is assigned to agent 1 , which is associated with the lowest $P_{i j}$, even though the corresponding $c_{i j}$ is not the lowest currently feasible for task 2. This shows how, as $Q$ increases, VAMI becomes increasingly biased toward assignments that make especially good use of resources. Thus, the status of the problem is:
(40) (87) $60 * 79$
$c_{i j}:$

| 89 | 63 | 58 | 10 |
| :--- | :--- | :--- | :--- |

$$
\begin{aligned}
& \text { slack } \\
& \mathrm{b}_{i k}:
\end{aligned}
$$

(61) (16) $72 * 43$

63
$a_{i j k}: \begin{array}{llll}19 & 46 * & 50 & 115 \\ 48 & 28 & 49 & 67\end{array}$

Since agent 1 has become infeasible for task 3, the penalties are recalculated as:

$$
H_{j}: * * * * \quad 9993911
$$

and task 3 is assigned to agent 2. This forces the assignment of task 4 to agent 1 because of resource limitations, giving:
(40) (87) 60 (79
$c_{i j}$ :
$8 9 6 3 \longdiv { 5 8 } 1 0$

> slack
$\mathrm{b}_{\mathrm{ik}}$ :
(61) (16) 72 (43) 20
(19) (16) 46 (50) 65
$a_{i j k}:$
$48 \quad 28$ (49) 67
101
$36 \quad 62$ 51 81 79

The total cost of this solution is 264 , which compares well with the optimum of 240 .

Increasing $Q$ above 0.7 causes a solution to be generated that is similar to the above except that task 1 is assigned to agent 2 . The cost of that alternative would be an unattractive 313.

VAMI did not find the optimum for this example (as RANDC did), but it did produce three feasible solutions, two of which were very near the optimum.

Narrative Description of LPMAX

Despite the apparent complexity of LPMAX, the basic logic is fairly simple. Any $x_{i j}=1$ indicates that the corresponding assignment can be made immediately. Tasks that remain unassigned are optimized in random order exactly as in RANDC, except that elements of $W$ corresponding to nonzero $x_{i j}$ are set equal to $x_{i j}$ instead of $c_{i j}$.

## Outline of LPMAX

It is assumed that a continuous optimum solution is available for a problem identical to Figure 2 except for relaxation of the zero-one constraint (2-4) to allow $x_{i j}$ to take on any value from zero to one.
I. Initialization.
A. Acquire $N, d$, and $X_{i j}$ 's for all $i$ and $j$.
B. For all $\mathbf{j}$ :

1. For all i;
a. If $x_{i j}=1$ :
(1) Store $j$ in right-hand end of $T$ (starting at $T_{n}$ ).
(2) Set $X_{j}=i$
(3) Go to I.B.1. for next j.
2. (All $x_{i j}$ known to be $\neq 1$ for this $j$ ): Store $j$ in lefthand end of $T$ (starting at $T_{1}$ ).
II. Generate N solutions.
A. Set $u$ and $Z$ to zero, set $B_{i k}=B_{i k}$ for $a l l i$ and $k$.
B. Shuffle left-hand indices in $T$.
C. For all $j=(n, n-1, \ldots, 2,1)$ (note right-to-left order).
3. Set $J=T_{j}$.
4. If right-hand $j$, go to II.C.4.
5. If left-hand $j$ :
a. For all i:
(1) $\quad$ Set $W_{i}=1000\left(1-x_{i j}\right)$.
(2) If $W_{i}=0$, set $W_{i}=1000+c_{i j}$.
b. For all i:
(1) Set $I$ to index of ith-smallest $W_{i}$.

> (a) If $a_{I J k}$ exceeds $B_{I k}$ for some $k$, go to II.C.3.b.(2).
> (b) If not, subtract $a_{I J k}$ from $B_{I k}$ for all $k$.
> (c) Set $C=c_{I J}$ and go to II.D.4.
> (2) If $\mathrm{i}<\mathrm{m}$, go to II.C.3.b.(1) for next $i$.
> $\begin{aligned} & \text { (3) If not, set } C=n \operatorname{Max}_{i, j}\left(c_{i j}\right) \text {; set } I=-1 \text {; add } \\ & 1 \text { to } u \text {. }\end{aligned}$
> 4. Add $C$ to $Z$, set $X_{J}=I$.
> D. Print first five solutions and all new best solutions.
E. Go to II.A.

GREEDY/CRAFTY

These two methods are flowcharted together in Figure 8, where reference is made to "RH" (right-hand) and "LH" (left-hand) tasks, which are the two tasks being considered for changes in agent assignment. The methods terminate when a complete cycle through all possible changes produces none that are feasible and profitable. A cycle addresses all (left-hand) tasks from 1 to $n-1$. For each of these, a trial agent is chosen. Then, each (right-hand) task of higher index than the left-hand task is examined to see if it is feasible for its assignment to be switched to some trial agent giving a lower objective function value in conjunction with the trial agent for the other task. In GREEDY, the change is made immediately, but CRAFTY makes the best change found in the entire cycle. Both methods then begin a new cycle.


Figure 8. Flowchart of GREEDY/CRAFTY

## BASIC METHODS PROGRAMMED AND TESTED

Introduction

This chapter describes the programming and testing of the basic methods of Chapter III, as well as auxiliary routines written to facilitate testing.

## Programs

## Languages

A11 programs are written in FORTRAN IV, except that continuous solutions are produced by IBM's MPS (Mathematical Programming System). Organization

Each solution method is programmed as a subroutine named SOLVER, which is called as part of an overall testing scheme which is flowcharted in Figure 9. A small main program directs the first step of the scheme through a housekeeping and control routine SOLOOP from which SOLVER is called. Before calling SOLOOP, the main program uses other subroutines to randomly generate (MATGEN) and print (MATPRT--optional) problems. After SOLOOP, another optional subroutine (MPSGEN) can be called to create a data set for input to MPS in the second step of the scheme. SOLVER calls SWAPPR, which is optionally GREEDY or CRAFTY.


Figure 9. Flowchart of Testing Scheme for Programmed Basic Solution Methods

The following paragraphs outline or describe each test routine.

## Outline of Main Program

I. Read control variables:
A. NOVBLS: Indicates end-of-file if greater than 9000.
B. ISEED: Seed for random-number function (RANDU).
C. IPRINT: Print switch; controls degree of detail in printout.
D. NBIGQS: " N " or " q " from Figure 7, depending on method used by SOLVER.
E. MTEST: Passed to SOLOOP to control number of solutions produced (one for each set of $b_{i k}$ right-hand-side values), and (optional--used with LPMAX) ${ }^{\text {reading }}$ of $\mathrm{x}_{\mathrm{ij}}$ values from a previous continuous solution.
F. LPFLAG: Controls calling of MPSGEN (see below). LPFLAG $=0:$ MPSGEN not called. LPFLAG $=1:$ MPSGEN called after SOLVER runs. LPFLAG $=2$ 2: Prevents SOLOOP from calling SOLVER; only MPSGEN is called.
G. IGREED: Controls method used in SWAPPR. IGREED $=0$ : No improvement is attempted. IGREED $=1: \quad$ GREEDY. IGREED $=2: \quad$ CRAFTY.
H. MM,NN, PP: Problem dimensions ( $m, n, p$ in Figure 2).
II. Call MATGEN to generate problem.
III. Cal1 MATPRT if IPRINT $=1$.
IV. Call SOLOOP to call SOLVER for several sets of $b_{i k}$ values.
V. Call MPSGEN to generate MPS problem data (unless LPFLAG is zero).

Outline of MATGEN
I. Generate $c_{i j}$ and $a_{i j k}$ values as integers distributed $U(1,1000)$.
II. Generate number of infeasibilities as an integer distributed $\mathrm{U}(1, \mathrm{mn} / 3)$.
III. Generate indices of infeasibilities as integers distributed (row) $U(1, m)$ or (column) $U(1, n)$.
IV. Flag infeasibilities: $c_{i j}=9999 ; a_{i j k}=0$.

## Outline of MATPRT

I. Print matrix of $c_{i j}$ values.
II. For each $k$, print matrix of $a_{i j k}$ values.

Outline of SOLOOP
I. If all agents are infeasible for some task, restore feasibility for a randomly chosen agent.
II. Find and print unconstrained optimum and resources required for it by each agent. This determines maximum $b_{i k}$ value (IBSTOP) to be tried in V. below.
III. Return to Main Program if LPFLAG $=2$ (i.e., MPS data are only output wanted; see I.F. in Outline of Main Program, above).
IV. Calculate cost of unassigned task as $n \cdot{ }_{i, j}^{\operatorname{Max}}\left(c_{i j}\right)$.
V. Control generation of solutions:
A. Check MTEST to control handling of $b_{i k}$ values and (optional; used with LPMAX) input of ${ }^{1 k}$ optimal continuous $\mathrm{x}_{i j}$ values produced by MPS. A11 $\mathrm{b}_{\mathrm{ik}}$ will be equal (variable name: IB) to facilitate testing.

MTEST $=0$ : Takes 11 steps in $1 B$ from $50 p(n / m+1)$ to IBSTOP (see II. above).

MTEST > 0: MTEST is the number of values of IB that are tried. Each IB is read from a card.

MTEST < 0: The negative of MTEST is again the number of IB's that are tried. However, after each IB, a deck of cards is read which contains $i, j$, and [1000 $\mathrm{x}_{\mathrm{ij}}$ ] for each nonzero $\mathrm{x}_{\mathrm{ij}}$ in an earlier MPS solution for the IB just read.
B. For each IB:

1. Finds and prints unconstrained optimum when $I B<1000$. Because $a_{i f}$ is distributed $U(1,1000)$, this gives a tighter bound on the optimum than calculations in II. above.
2. Calls SOLVER to obtain a solution for $a l l b_{i k}=I B$.

## Description of MPSGEN

The flow of MPSGEN is determined by the sequence required for MPS input data, an example of which can be found in Appendix B. The output of MPSGEN can be related to Figure 2 as follows:

| MPS Data Item | Notation in Figure 2 |
| :--- | :--- |
| Row R00000 | Objective Function (2-1) |
| Row R1iiik | Resource Constraints (2-2) |
| Row R2jjj | Coverage Constraints (2-3) |

Column Xliiijj ( $\mathrm{n}<100$ )
$x_{i j}$
Column Xliijjj( $\mathrm{n}>99$ )
$X_{i j}$

The unmodified output of MPSGEN can be used by MPS in the next job step.

## Description of SOLVER

SOLVER is coded using symbolic names that are either self-explanatory or coincide as closely as possible with Figures 2 and 7. Figure 10 establishes correspondence between Figures 2 and 7 and the code of SOLVER (see Appendix A). Four versions of SOLVER were prepared: RANDC, RANDR, LPMAX, VAMI. Each version of SOLVER uses logic that is similar to the corresponding outline in Chapter III. The main exception is the use of IB for all $b_{i k}$, which greatly facilitates testing without (because $a_{i j k}$ are random variables) introducing undesirable bias into the testing process. Each SOLVER can be easily recoded to use $b_{i k}$ values passed in an array. The solutions found by SOLVER will be printed with a degree of detail that depends on the value stored in IPRINT:

| Symbol in Figures 2 and 7 | Variable Name(s) in Appendix |
| :---: | :---: |
| a | AV (vector form), A(matrix) |
| A | AB |
| b | IB |
| B | BV, B |
| c | CV, C |
| C | CBIG |
| d | ISEED |
| F | F |
| H | H |
| $i$ | I |
| I | IBIG |
| j | J |
| J | JBIG |
| k | K |
| m | MM (object-time dimension, M (operational) |
| n | NN, N |
| N | NBIGQS |
| p | PP, P |
| P | PS |
| q | NBIGQS |
| Q | Q |
| S | S |
| T | T |
| u | U |
| W | W |
| X | XB |
| Z | Z |
| $\mathrm{Z}_{\text {min }}$ | MINZ |

Figure 10. Symbols From Figures 2 and 7 Corresponding to Variable Names in Appendix A

# IPRINT = 1: The first 5 solutions and all new best solutions are printed in long form. This includes the value of the objective function ("COST"), the number of tasks remaining unassigned ("NO UNASGD TASKS"), the sum of the $C_{i j}$ values for the assigned tasks ("COST OF ASGD TASKS"), and the number of trials necessary for SOLVER to obtain the solution ("TRIAL NO."), all on a single line. The next line begins with the words "ASSIGNMENT VECTOR:" followed by $X_{1}$ through $X_{20}$, with additional lines being used as needed for $X_{21}$ through $X_{n}$. Then the slacks (each agent's remaining supply of each resource) are printed. <br> IPRINT $=0:$ Identical to IPRINT $=1$, except that new best solutions are the only ones printed. <br> IPRINT $=-1$ : This also causes output to be printed only for new best solutions, but in short form, where the slacks are not printed. <br> SWAPPR is called to try to improve any new best solution. If IGREED $=0$ SWAPPR will take no action. However, even if IGREED $=0$, it will be set to 1 to let GREEDY attempt to improve the best solution found by SOLVER for each value of $b_{i k}$. VAMI uses a subroutine named A PENCOL to obtain or recalculate the penalty for each task. 

## Description of SWAPPR

This subroutine follows the logic of Figure 8. The code of SWAPPR in Appendix A refers to six important indices:

JL (JR) Index of left (right) -hand task
IL (IR) Index of agent to which left(right)-hand task is currently assigned

IL2 (IR2) Index of trial agent for left(right)-hand task
The fundamental decision of SWAPPR is to determine if a cost savings can be attained without violating any resource constraints if the assignment of task JL is switched from agent IL to agent IL2 while
switching task JR from agent IR to agent IR2.
Improvement methods can be used in a "stand-alone" mode if an initial solution is made available to SWAPPR for improvement. Description of RANDU

RANDU is a multiplicative congruential generator of pseudorandom variates distributed $U(0,1)$. It was adapted as a FORTRAN FUNCTION from the well-known subroutine RANDU found in IBM's Scientific Subroutine Package. The modification used in Appendix A was designed for maximum speed, but retains the statistical characteristics of the original RANDU. RANDU is machine-dependent, as are almost all such routines, and will probably need to be rewritten if not implemented on a computer similar to the IBM $360 / 370$ series.

## Continuous Solutions with MPS

MPS is implemented in a straight-forward manner, as can be seen from the code in Appendix A. The only extension beyond the simplest minimization of a linear program is the use of the "BOUND" option to "SETUP" the relaxation of the zero-one constraint to bounded variables. In this work, the output of MPSGEN has always been passed to MPS as a temporary data set. This is easily accomplished using Job Control cards, and is much more convenient than handling the thousands of data cards required to describe the continuous form of a thousand-variable program with several resources.

Passing the Results of MPS to LPMAX

Usually, almost all variable values produced by MPS are zeros. A typical problem with 50 tasks might have only $55-65$ nonzero $x_{i j}{ }^{\prime}$ s in


#### Abstract

its continuous solution, depending on tightness of constraints, even though the total number of variables might be 1000 or more. This makes it fairly convenient to manually prepare input cards for testing LPMAX.


Testing the Programs

## Preliminary Testing

Initially, several problems of various dimensions were run in order to decide on the design of further testing procedures. For most problems, RANDC, VAMI (which includes VAMC), and LPMAX were allowed to produce several solutions each, with their best solutions being improved by GREEDY and CRAFTY. GREEDY and CRAFTY were also used in the "stand-alone" mode by allowing RANDC to generate one solution which was then passed to SWAPPR for improvement. Finally, as aids to evaluation, RANDC and RANDR were run for large values of $N$ and succeeded by GREEDY. The continuous optimum produced for LPMAX and the unconstrained zero-one optima found by SOLOOP also served as evaluation standards. Several general observations were made.

## Execution Time

Not surprisingly, this seemed to be a function of the number of variables (mn), the "shape" (ratio of $m$ to $n$ ), and the number of resources (p). Different methods appeared to be affected quite differently by these factors, however. GREEDY and CRAFTY are too slow to use on large problems, even for test purposes.

## Objective Function Values

In this respect, the construction heuristics were consistently closer (in percentage) to a bound on the optimum for large (mn $=0(1000)$ ) problems than for small, which was unexpected. However, this became less surprising after calculations revealed that the average difference among all possible objective values is many magnitudes less for a large problem than for a small one. Consider the following example of two problems of the same shape but different size:

Dimensions (m x n): $7 \times 5 \quad 35 \times 25$
No. Solutions $\left(m^{n}\right)$ :
$1.6 \times 10^{4}$
$4.0 \times 10^{38}$
Worst Solution
(All Tasks Unassigned): 25000625000

Best Solution (Unconstrained Optimum): 1639580

Average Difference Between Solutions: 1.4 $1.6 \times 10^{-33}$ but a similar analysis based only on feasible solutions is not a reasonable undertaking, and it is doubtful if the results would differ significantly.

Feasibility

Where feasible solutions were known to exist, construction heuristics seemed to be a bit better at finding them for large problems than for small ones. Again, there are probably enormously greater numbers of feasible solutions to a large problem.

## Problem Characteristics

It was clearly impossible to test all methods thoroughly with several problems in each category of characteristics. Suppose five different problem sizes were tested for six different shapes with five different sets of $b_{i k}$ values for from one to four resources, using each basic method, with GREEDY and CRAFTY being applied to the final result of each construction heuristic, along with the use of RANDC and RANDR for very large values of $N(2000)$ to obtain a solution that would be 99.7 percent sure to lie in the .997 quantile of all solutions. Even without multiple replication, thousands of computer runs would be required, many of which would cost over $\$ 100$ each. The testing of programs would require several years, and several rooms could be filled with the printouts.

From the preliminary testing, it appeared that there were pronounced performance differences between the methods. Therefore, it was decided that an extensive testing procedure as described above would reveal very little that could not be inferred from an abbreviated scheme. Each problem characteristic was considered from the standpoint of its importance in revealing differences in the performance of methods relative to each other.

## Problem Size

This characteristic had great effect on performance during preliminary testing, but the effect appeared to be purely linear (construction) or quadratic (improvement). Relative performance between methods seemed to be almost the same for small and large problems.

Therefore, it was decided to do almost all further testing for problems with approximately (1) 50 , or (2) 1000 variables. Other problem sizes would only be "spot-checked."

Problem Shape

This seemed to be a very important characteristic, so it was decided to try five or six shapes for each problem size. However, it appeared that "tall" problems ( $\mathrm{m} / \mathrm{n}$ of, say, three or more) gave identical objective values with any method. There were usually strong indications that these results were optimal. Therefore, more emphasis was placed on "wide" (m/n about 0.1) problems than on "tall" ones.

## Number of Resources

This affected LPMAX, CRAFTY, and GREEDY strongly, but made less difference with other methods. Also, it made little difference in the relative performance of the methods. Therefore, various values of $p$ were tried for most problems, with p being held constant for an occasional specialized test.

## Tightness of Constraints

Relative performance of methods appeared to depend on the degree to which problems were constrained, so it was decided to try several values of $b_{i k}$. To increase the chances of interesting results, one method (usually RANDC or VAMI) was run with MTEST $=0$, which caused 11 values of $b_{i k}$ to be tried. The other methods were then used with the (usually) four $b_{i k}$ values which appeared to be most likely to cause differences in relative performance of methods.

## Characteristics of Methods

These make it impossible to devise a "fair" way to compare methods. One obvious appraoch would be to allow each method equivalent time and storage (perhaps combined, e.g., kilobyte-hours) to work on identical problems. Also, methods could be allowed to run until equivalent solutions were produced. Neither of these approaches is fair because methods vary in their performance characteristics:
(1) Some methods (RANDC) can make better use of additional time than others (VAMI).
(2) Some methods (LPMAX) require a high initial investment of storage and time for the first solution, but subsequent solutions are produced very rapidly.
(3) There is no way to be sure that each method has been coded to use individual logic features as efficiently as possible.
(4) Each method is designed to use different amounts of time and/or storage in the hope of obtaining a solution whose quality is related to its cost.

Glover et a1. [14] also concluded that no "fair" comparison can be devised.

Some approach, however, had to be chosen. The considerations discussed in the last several pages led to the final test design, in which the "equal time" approach allowed RANDC the same time as needed by VAMI, while other methods were run so as to reveal if their results justified their cost. Results were compared from many viewpoints.

## Test Design

RANDC was run for approximately the time needed by VAMI for $q=11$.

LPMAX and GREEDY were run as seemed "natural" for them:
(1) LPMAX was run for $\mathrm{N}=10$ after being allowed the tremendous overhead of MPS.
(2) GREEDY was run to completion with an initial solution produced by RANDC for $\mathrm{N}=1$. GREEDY was not tested for large problems. Most of each test run was devoted to obtaining evaluation standards. Problem size determined what could be done:
(1) Small problems, where $\mathrm{mn}=0(50)$ :
(a) RANDR and RANDC were run for $\mathrm{N}=2000$.
(b) GREEDY was used to attempt to improve the results obtained by each other method.
(2) Large problems, where $\mathrm{mn}=0(1000):$
(a) RANDR and RANDC were usually run for $\mathrm{N}=500$, although several runs were made for $\mathrm{N}=2000$.
(b) No improvement with GREEDY was attempted. A single run would have cost about \$200.
(3) SOLVER calculated the unconstrained optimum.
(4) MPS gave the continuous optimum. Not only the solution value was used, but also the fraction of nonzero $x_{i j}$ that were equal to one. This fraction seemed to be a good indicator of constraint severity, since no method (in preliminary testing) ever found a way to cover all tasks when this fraction was below one-half.

## Summary of Test Runs

("Run" means one execution of the scheme described above in Test Design for one set of $b_{i k}$ values.) A total of 107 runs were made- 66 for small problems (only 47 and 53 of these included LPMAX and GREEDY,
respectively) and 41 for large problems. Of the 107 test runs, 42 were intended to produce results for detailed tabulation to allow direct comparison of relative performances of the various methods. These 42 runs were made for eleven different problems by using four (two with Problem 5) sets of $b_{i k}$ values for each problem. The results are displayed in Tables II through XII and summarized in Table I.

TABLE I
SUMMARY OF PROBLEM RESULTS

| Problem/Table | Size (mn) | m | n | p | Number of $\mathrm{b}_{\text {ik }}$ Values |
| :---: | ---: | ---: | ---: | ---: | :---: |
| 1/II | 48 | 4 | 12 | 4 | 4 |
| 2/III | 50 | 5 | 10 | 1 | 4 |
| 3/IV | 49 | 7 | 7 | 3 | 4 |
| 4/V | 48 | 6 | 8 | 1 | 4 |
| 5/VI | 48 | 8 | 6 | 3 | 2 |
| 6/VII | 48 | 3 | 16 | 4 | 4 |
| 7/VIII | 1000 | 10 | 100 | 2 | 4 |
| 8/IX | 1000 | 20 | 50 | 3 | 4 |
| 9/X | 992 | 31 | 32 | 1 | 4 |
| 10/XI | 1000 | 40 | 25 | 3 | 4 |
| 11/XII | 1000 | 50 | 20 | 4 | 4 |

The other 65 runs were used in part to investigate special performance characteristics of methods. All runs were used in summary tabulations.

## Test Results

## General

The following paragraphs present and discuss summary tabulations of test results based on all 107 test runs. Discussions of special

TABLE II

TEST RESULTS FOR PROBLEM 1

| $\frac{\text { No．Variables }}{48(4 \times 12)}$ | No．Resources |  |  |  | $\begin{gathered} \frac{\text { Seed (RANDU) }}{7001} \\ \text { Avg. CPU } \\ \text { Time (sec.) } \\ \text { per } \mathrm{b}_{\mathrm{ik}} \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | $\mathrm{u}^{1} \mathrm{Z}_{\text {min }}$ ob | ined for |  |  |
| Methods／Trials | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}= \\ & 1370 \end{aligned}$ | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}= \\ & 1940 \end{aligned}$ | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}= \\ & 2130 \end{aligned}$ | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}= \\ & 2510 \end{aligned}$ |  |
| RANDC／30 | 3，38613 | 0，4222 | 0，3385 | 0，3381 | 0.3 |
| ＋GREEDY | Same | 0，4107 | Same | Same | 0.5 |
| VAMC | 5，62413 | 1，15220 | 0，3385 | 0，3381 | －－ |
| VAMI／11 | 4，51676 | 0，4347 | 0，3385 | 0，3381 | 0.3 |
| ＋GREEDY | 3，39753 | Same | Same | Same | 0.5 |
| LPMAX／10 | 3，40101 | 1，14524 | 0，3385 | 0，3381 | 5.3 |
| ＋GREEDY | Same | Same | Same | Same | 0.4 |
| GREEDY | 4，49188 | 0，4107 | 0，3385 | 0，3381 | 0.6 |
| RANDR／2000 | 2，30401 | 0，4756 | 0，3922 | 0，3801 | 15.1 |
| ＋GREEDY | 2，28571 | 0，3913 | 0，3385 | 0，3466 | 0.5 |
| RANDC／2000 | 3，38613 | 0，4107 | 0，3385 | 0，3381 | 16.2 |
| ＋GREEDY | Same | Same | Same | Same | 0.4 |
| CONTINUOUS | 5760.4 | 3374.7 | 3338.2 | 3318.6 | 5.0 |
| OPTIMUM $⿰ ⿰ 三 丨 ⿰ 丨 三 \mathrm{x}_{\mathrm{ij}}=1 / \\| \mathrm{x}_{\mathrm{ij}} \neq 0$ | 3／21 | 9／15 | 10／14 | 11／13 |  |
| UNCONSTRAINED OPTIMUM | 0，3284 | 0，3284 | 0，3284 | 0，3284 |  |

TABLE III
TEST RESULTS FOR PROBLEM 2

| $\frac{\text { No．Variables }}{50(5 \times 10)}$ | No．Resources |  |  |  | $\begin{gathered} \frac{\text { Seed (RANDU) }}{1122334455} \\ \text { Avg. CPU } \\ \text { Time (sec.) } \\ \text { per } \mathrm{b}_{\mathrm{ik}} \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{u}, \mathrm{z}_{\text {min }}$ obtained for： |  |  |  |  |
|  |  |  |  |  |  |
| Methods／Trials | $\begin{array}{r} \mathrm{b}_{i \mathrm{k}}= \\ 310 \end{array}$ | $\begin{aligned} & \mathrm{b}_{i k}= \\ & 470 \end{aligned}$ | $\begin{aligned} & b_{i k}= \\ & 550 \end{aligned}$ | $\begin{gathered} \mathrm{b}_{i k}= \\ 630 \end{gathered}$ |  |
| RANDC／30 | 3，30706 | 1，11777 | 0，2844 | 0，2482 | 0.2 |
| ＋GREEDY | Same | 1，11759 | 0，2810 | Same | 0.4 |
| VAMC | 3，30531 | 2，20580 | 0，2996 | 0，2482 |  |
| VAMI／11 | 3，30631 | 1，12194 | 0，2844 | 0，2482 | 0.2 |
| ＋GREEDY | Same | Same | 0，2810 | Same | 0.4 |
| LPMAX／10 |  | 2，22376 | 0，2844 | 0，2842 | 3.6 |
| ＋GREEDY |  | 1，12862 | 0，2810 | 0，2482 | 0.4 |
| GREEDY | 3，30531 | 1，11759 | 1，11618 | 1，11759 | 0.8 |
| RANDR／2000 | 3，30531 | 1，11777 | 0，2844 | 0，2482 | 14.3 |
| ＋GREEDY | Same | 1，11759 | 0，2810 | Same | 0.4 |
| RANDC／2000 | 3，30531 | 1，11777 | 0，2844 | 0，2482 | 16.2 |
| ＋GREEDY | Same | 1，11759 | 0，2810 | Same | 0.4 |
| CONTINUOUS | Infeasible | 2711.5 | 2342.0 | 2228.3 | 3.2 |
| OPTIMUM $⿰ ⿰ 三 丨 ⿰ 丨 三 \mathrm{x}_{\mathrm{ij}}=1 / \# \mathrm{x}_{\mathrm{ij}} \neq 0$ |  | 6／14 | 7／13 | 8／12 |  |
| UNCONSTRAINED OPTIMUM | 0，2370 | 0，2183 | 0，2175 | 0，2175 |  |

TABLE IV

TEST RESULTS FOR PROBLEM 3


TABLE . V

TEST RESULTS FOR PROBLEM 4

| No. Variables | No, Resources |  |  |  | $\frac{\text { Seed (RANDU) }}{3001}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $48(6 \times 8)$ |  | u, z | tained for |  |  |
| Methods/Trials | $\begin{gathered} \mathrm{b}_{\mathrm{ik}}= \\ 580 \end{gathered}$ | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}= \\ & 740 \end{aligned}$ | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}= \\ & 1220 \end{aligned}$ | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}= \\ & 1380 \end{aligned}$ | $\begin{gathered} \text { Time (sec.) } \\ \text { per } b_{i k} \end{gathered}$ |
|  |  |  |  |  |  |
| RANDC/30 | 1,10246 | 0,2503 | 0,1439 | 0,1439 | 0.2 |
| + GREEDY | Same | Same | Same | Same | 0.3 |
| VAMC | 1,10246 | 0,2503 | 0,1439 | 0,1439 | -- |
| VAMI/11 | 1,10246 | 0,2503 | 0,1439 | 0,1439 | 0.2 |
| + GREEDY | Same | Same | Same | Same | 0.3 |
| LPMAX/10 |  | 1,9963 | 0,1494 | 0,1439 | 3.3 |
| + GREEDY |  | 0,2503 | 0,1439 | Same | 0.4 |
| GREEDY | 1,10246 | 0,2503 | 0,1439 | 0,1439 | 0.4 |
| RANDR/2000 | 1,10246 | 0,2503 | 0,1494 | 0,2048 | 8.9 |
| + GREEDY | Same | Same | 0,1439 | 0,1508 | 0.4 |
| RANDC/2000 | 1,10246 | 0,2503 | 0,1439 | 0,1439 | 13.8 |
| + GREEDY | Same | Same | Same | Same | 0.3 |
| CONTINUOUS | Infeasible | 2499.3 | 1273.7 | 1218.1 | 3.1 |
| OPTIMUM |  | 7/9 | 7/9 | 7/9 |  |
| $\# x_{i j}=1 / \# x_{i j} \neq 0$ |  |  |  |  |  |
| UNCONSTRAINED |  |  |  |  |  |
| OPTIMUM | 1,9914 | 0,2489 | 0,1137 | 0,1137 |  |

## TABLE VI

TEST RESULTS FOR PROBLEM 5

| No. Variables | No. Resources |  | Seed (RANDU) |
| :---: | :---: | :---: | :---: |
| 48(8×6) | $\mathrm{u}, \mathrm{Z}_{\min } \text { obtained for: }$ |  | ```1357 Avg. CPU Time (sec.) per b}\mp@subsup{\textrm{b}}{\textrm{ik}}{``` |
|  |  |  |  |
|  | $\mathrm{b}_{\text {ik }}=$ | $\mathrm{b}_{i k}=$ |  |
| Methods/Trials | 790 | 870 |  |
| RANDC/30 | 0,1963 | 0,1635 | 0.2 |
| + GREEDY | Same | Same | 0.5 |
| VAMC | 0,1963 | 0,1635 |  |
| VAMI/11 | 0,1963 | 0,1635 | 0.2 |
| + GREEDY | Same | Same | 0.5 |
| LPMAX / 10 | 0,1963 | 0,1635 | 3.9 |
| + GREEDY | Same | Same | 0.5 |
| GREEDY | 0,1963 | 0,1635 | 0.5 |
| RANDR/2000 | 0,1963 | 0,1635 | 15.1 |
| + GREEDY | Same | Same |  |
| RANDC/2000 | 0,1963 | 0,1635 | 21.7 |
| + GREEDY | Same | Same | 0.5 |
| CONTINUOUS | 1962.2 | 1554.9 | 3.7 |
| OPTIMUM | 5/7 | 4/8 |  |
| $\# x_{i j}=1 / \# k_{i j} \neq 0$ |  |  |  |
| UNCONSTRAINED | 0,1958 | 0,1499 |  |
| OPTIMUM |  |  |  |

## TABLE VII

TEST RESULTS FOR PROBLEM 6

| $\frac{\text { No. Variables }}{48(3 \times 16)}$ | No. Resources |  |  |  | $\frac{\text { Seed (RANDU) }}{13579}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  |
|  | $\mathrm{u}, \mathrm{Z}$ obtained for: |  |  |  |  |
|  | $\mathrm{b}_{\mathrm{il}}=$ | b | $\mathrm{b}_{\mathrm{il}}=$ | $\mathrm{b}_{\mathrm{il}}=$ | $\begin{aligned} & \text { Avg. CPU } \\ & \text { Time (sec.) } \\ & \text { per } b_{1 k} \end{aligned}$ |
| Methods/Trials | $2700$ | $3300$ | $3600$ | 18000 |  |
| RANDC/30 | 2,36291 | 1,20996 | 0,5121 | 0,5121 | 0.3 |
| + GREEDY | 2,35202 | Same | Same | Same | 0.6 |
| VAMC | 3,51799 | 0,5624 | 0,5121 | 0,5121 | -- |
| VAMI/11 | 3,51777 | 0,5624 | 0,5121 | 0,5121 | 0.9 |
| + GREEDY | 2,36209 | 0,5454 | Same | Same | 0.6 |
| LPMAX/10 |  | 1,20996 | 0,5121 | 0,5121 | 4.4 |
| + GREEDY |  | Same | Same | Same | 0.6 |
| GREEDY | 3,50603 | 0,6001 | 0,5154 | 0.5121 | 0.6 |
| RANDR/2000 | 2,35921 | 0,6263 | 0,5727 | 0,5313 | 23.9 |
| + GREEDY | Same | 0,5361 | 0,5295 | 0,5163 | 0.6 |
| RANDC/2000 | 2,35651 | 0,5945 | 0,5121 | 0,5121 | 24.7 |
| + GREEDY | 1,20305 | Same | Same | Same | 0.6 |
| CONTINUOUS | Infeasible | 5206.9 | 5084.1 | 5027.7 | 4.1 |
| OPTIMUM |  | 14/18 | 15/17 | 15/17 |  |
| $\# \mathrm{x}_{\mathrm{ij}}=1 / \not / \not \mathrm{x}_{\mathrm{ij}} \neq 0$ |  |  |  |  |  |
| UNCONSTRAINED OPTIMUM | 0,4989 | 0,4989 | 0,4989 | 0,4989 |  |

TABLE VIII
TEST RESULTS FOR PROBLEM 7

| $\frac{\text { No. Variables }}{1000(10 \times 100)}$ | No. Resources |  |  |  | $\begin{gathered} \frac{\text { Seed (RANDU) }}{1007} \\ \text { Avg. CPU } \\ \text { Time (sec.) } \\ \text { per } \mathrm{b}_{\mathrm{ik}} \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{u}, \mathrm{z}_{\text {min }}$ obtained for: |  |  |  |  |
|  | $\begin{aligned} & b_{i k}= \\ & 4140 \end{aligned}$ | $\begin{aligned} & b_{i k}= \\ & 4900 \end{aligned}$ | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}= \\ & 5660 \end{aligned}$ | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}{ }^{\mathrm{n}} \\ & 7180 \end{aligned}$ |  |
| RANDC/500 | 3,320139 | 0,11867 | 0,9694 | 0,8856 | 30.8 |
| VAMC | 7,714355 | 0,10979 | 0,9466 | 0,8856 | 30.1 |
| VAMI/11 | 0,13800 | 0,10148 | 0,9320 | 0,8856 |  |
| LPMAX/10 | 1,113622 | 0,12156 | 0,9388 | 0,8856 | 63.8 |
| RANDR/2000 | 1,145341 | 0,422101 | 0,41651 | 0,40820 | 123.2 |
| RANDC/2000 | 2,217867 | 0,11715 | 0,9551 | 0,8856 | 205.0 |
| CONTINUOUS | 12968.3 | 9916.5 | 9272.4 | 8854.3 | 60.4 |
| OPTIMUM $\\| x_{i j}=1 / \# x_{i j} \neq 0$ |  |  |  |  |  |
| UNCONSTRAINED OPTIMUM | 0,8829 | 0,8829 | 0,8829 | 0,8829 |  |

TABLE IX

TEST RESULTS FOR PROBLEM 8

| No. Variables | No. Resources |  |  |  | $\frac{\text { Seed (RANDU) }}{121341}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1000 (20 x 50) | u, z obtained for: |  |  |  |  |
|  | $\mathrm{b}_{\text {ik }}=$ | $\mathrm{b}_{\text {ik }}=$ | $\mathrm{b}_{i k}=$ | $\mathrm{b}_{\mathrm{il}}=$ | ```Avg. CPU Time (sec.) per \(b_{i k}\)``` |
| Methods/Trials | 1440 | 1770 | 2430 | 2760 |  |
| RANDC/125 | 0,7184 | 0,4445 | 0,3075 | 0,2914 | 12.2 |
| VAMC | 0,7149 | 0,3874 | 0,2958 | 0,2880 | -- |
| VAMI/11 | 0,5587 | 0,3632 | 0,2958 | 0,2880 | 12.0 |
| LPMAX/10 | 0,7027 | 0,3910 | 0,3115 | 0,2880 | 82.3 |
| RANDR/2000 | 0,20501 | 0,19012 | 0,17401 | 0,17936 | 83.8 |
| RANDC/2000 | 0,6107 | 0,4138 | 0,3010 | 0,2880 | 198.0 |
| CONTINUOUS | 5203.3 | 3444.6 | 2902.2 | 2876.5 | 75.7 |
| OPTIMUM | 43/57 | 45/55 | 48/52 | 48/52 |  |
| $⿰ \mathrm{x}_{\mathrm{ij}}=1 / \not \equiv \mathrm{x}_{\mathrm{ij}} \neq 0$ |  |  |  |  |  |
| UNCONSTRAINED OPTIMUM | 0,2761 | 0,2761 | 0,2761 | 0,2761 |  |

TABLE X

## TEST RESULTS FOR PROBLEM 9

| $\frac{\text { No. Variables }}{992(31 \times 32)}$ | No. Resources |  |  |  | $\frac{\text { Seed (RANDU) }}{380225}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{u}, \mathrm{Z}_{\min } \text { obtained for: }$ |  |  |  | 380225 <br> Avg. CPU |
| Methods/Trials | $\begin{gathered} \mathrm{b}_{\mathrm{ik}}= \\ 100 \end{gathered}$ | $\begin{gathered} \mathrm{b}_{\mathrm{ik}}= \\ 290 \end{gathered}$ | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}= \\ & 860 \end{aligned}$ | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}= \\ & 1620 \end{aligned}$ | $\begin{aligned} & \text { Time (sec.) } \\ & \text { per } b_{i k} \end{aligned}$ |
| RANDC/30 | 4,137693 | 0,5135 | 0,1519 | 0,1088 | 5.0 |
| VAMC | 3,106635 | 0,4988 | 0,1572 | 0,1088 | -- |
| VAMI/11 | 3,106635 | 0,4988 | 0,1556 | 0,1088 | 5.1 |
| LPMAX/10 |  | 0,5217 | 0,1581 | 0,1088 | 60.6 |
| RANDR/500 | 3,109018 | 0,12591 | 0,11693 | 0,10823 | 19.8 |
| RANDC / 500 | 3,106635 | 0,5021 | 0,1490 | 0,1088 | 83.5 |
| CONTINUOUS | Infeasible | 4597.2 | 1468.7 | 1086.2 | 55.4 |
| OPTIMUM |  | 28/36 | 31/33 | 31/33 |  |
| $\# x_{i j}=1 / \# x_{i j} \neq 0$ |  |  |  |  |  |
| UNCONSTRAINED OPTIMUM | 3,104636 | 0,4281 | 0,1230 | 0,1070 |  |

TABLE XI
TEST RESULTS FOR PROBLEM 10


TABLE XII
TEST RESULTS FOR PROBLEM 11

| No. Variables | No. Resources |  |  |  | Seed (RANDU) |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1000 (50 x 20) | $\mathrm{u}, \mathrm{Z}_{\text {min }}$ obtained for: |  |  |  | $\begin{aligned} & 121567 \\ & \text { Avg. CPU } \\ & \text { Time (sec.) } \\ & \text { per } \mathrm{b}_{\mathrm{ik}} \end{aligned}$ |
| Methods/Trials | $\begin{gathered} \mathrm{b}_{\mathrm{ik}}= \\ 520 \end{gathered}$ | $\begin{aligned} & \mathrm{b}_{i k}= \\ & 840 \end{aligned}$ | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}= \\ & 1320 \end{aligned}$ | $\begin{aligned} & \mathrm{b}_{\mathrm{ik}}= \\ & 1640 \end{aligned}$ |  |
| RANDC/45 | 0,6020 | 0,891 | 0,372 | 0,366 | 7.2 |
| VAMC | 0,6020 | 0,891 | 0,372 | 0,366 | -- |
| VAMI / 11 | 0,6020 | 0,891 | 0,372 | 0,366 | 7.1 |
| LPMAX/10 | 1,25721 | 0,891 | 0,372 | 0,366 | 99.5 |
| RANDR / 500 | 0,7515 | 0,6139 | 0,6823 | 0,6717 | 16.7 |
| RANDC / 500 | 0,6020 | 0,891 | 0,372 | 0,366 | 78.9 |
| CONTINUOUS | 5903.2 | 887.6 | 371.3 | 365.8 | 94.3 |
| OPTIMUM | 15/25 | 18/22 | 19/21 | 19/21 |  |
| $\# x_{i j}=1 / \# x_{i j} \neq 0$ |  |  |  |  |  |
| UNCONSTRAINED OPTIMUM | 0,5478 | 0,809 | 0,362 | 0,362 |  |

performance characteristics exhibited by individual methods are supported by results from selected runs.

## Tables II Through XII

The values tabulated are in the form $u, Z_{\text {min }}$ with $Z_{\text {min }}$ including the costs charged for the number of unassigned tasks (u). Several things stand out:
(1) VAMI and RANDC (allowed the same amount of time as VAMI) consistently gave better objective values and used less CPU time than LPMAX or GREEDY.
(2) Objective values found by all methods usually have a high probability of being in the uppermost percentile of all possible solutions, based on the value achieved by RANDR for $\mathrm{N}=2000$ or $\mathrm{N}=500$.
(3) All methods usually obtained feasible solutions, given existence, and near-optimal solutions, given bounds. GREEDY could not improve many of the solutions found by the construction heuristics.
(4) Problem characteristics (size, shape, number of resources, tightness of constraints) have great effect on absolute and relative performance of methods. RANDC gives much better results with small problems than with large, for example.

Specific measures of performance will be discussed in more detail below, based on results from all test runs.

## Pairwise Comparison on Solution Values

Table XIII shows the outcomes of comparing each pair of methods in terms of the objective function values achieved. The data below the diagonal are for large problems, where $m n=0(1000)$. Each entry in Table XIII consists of three numbers in the form $\mathrm{T}, \mathrm{L}, \mathrm{U}$ :

T: Total number of runs in which both methods were tested on a problem of a given size category.

L: Number of runs in which the Left-hand (row heading) method gave a better objective value.

U: Number of runs in which the Upper (column heading) method gave a better objective value.

For example, the entry $47,17,2$ at the intersection of the row labeled VAMI and the column labeled LPMAX means that both VAMI and LPMAX were tested on 47 runs of small problems, with VAMI obtaining a better solution than LPMAX in 17 runs, and LPMAX giving a better value than VAMI twice. Obviously the two methods gave the same solution 28 times.

TABLE XIII
OUTCOMES OF PAIRWISE COMPARISONS OF METHODS ON SOLUTION VALUES OBTAINED

|  | SMALL PROBLEMS |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | RANDC | VAMC | VAMI | LPMAX | GREEDY |
| RANDC | -- | $(66,18,7)$ | 66,14,8 | 47,20,0 | $(53,18,7)$ |
| VAMC | 41,20,4 | -- | 66,* ,15 | $(\overline{47,16,6)}$ | 53,16,8) |
| VAMI | 41,20,4 | 41,14,* | -_ | 47,17,2 | 53,16,7 |
| LPMAX | 41,14,14 | $(41,6,16)$ | 41,0,24 | -- | 47,9,17 |
| LARGE PROBLEMS |  |  |  |  |  |

In interpreting Table XIII, it should be noted that VAMC is the same as VAMI with $\mathrm{Q}=0$, so VAMC can never give a better solution than VAMI. This is indicated by asterisks where appropriate. Further, GREEDY was not used on large problems, as stated earlier.

Nonparametric sign tests were performed on the data of Table XIII. Each underlined entry indicates an observed significance leyel (OSL) of 0.05 or less. Parentheses denote an OSL between 0.05 and 0.10 . No
sign test was performed for the VAMC/VAMI comparison, since VAMI will always perform at least as well as VAMC.

From Table XIII, it is clear that VAMI is best for large problems using this criterion. For small problems, RANDC seems to be best, although it does not differ significantly from VAMI.

A weakness in this comparison technique is that solution values and differences between solutions are not quantified. This makes RANDC and LPMAX seem to perform equally on large problems. In fact, when LPMAX is better than RANDC, it is usually only a little better, but when it is worse, it is often much worse. This can be seen in Tables II through XII.

## Best Heuristic Solution

Table XIV shows how often each method gave the best objective value, including ties. Each entry in Table XIV is in the form $B / T$ ( $\mathrm{P} \%$ ) :

B: Number of Best solutions (or ties) produced by a given method.

T: Total number of runs involving all methods.
P: Percentage of $T$ represented by $B$. For example, the entry " $36 / 47$ (77\%)" for RANDC on a small problem means that in 36 of the 47 runs in which all methods were involved, RANDC gave a solution at least as good as the best obtained by any other method.

Table XIV can be seen as a table of estimates of the probability that one method will outperform or equal any other in terms of the objective value produced. Again, VAMI stands out for large problems, while the distinction between methods is not at all clear for small problems. The best and worst methods (RANDC and LPMAX/GREEDY) for small
problems differ by only 22 percent. This is less than the 24 percent difference between the two best methods for large problems (VAMI and VAMC), whose outcomes are not even independent of each other.

TABLE XIV
FREQUENCIES AND PERCENTAGES FOR BEST SOLUTIONS FROM INDIVIDUAL METHODS

|  | Small <br> Problems | Large <br> Problems |
| :--- | :---: | :---: |
| RANDC | $36 / 47(77 \%)$ | $14 / 41(34 \%)$ |
| VAMC | $32 / 47(68 \%)$ | $29 / 41(71 \%)$ |
| VAMI | $34 / 47(72 \%)$ | $39 / 41(95 \%)$ |
| LPMAX | $26 / 47(55 \%)$ | $14 / 41(34 \%)$ |
| GREEDY | $26 / 47(55 \%)$ | not tested |

VAMC appears to have performed well, since it found as good a solution as any other method for more than two-thirds of both large and small problems. However, many of its less-than-best solutions were very poor indeed, especially when constraints were tight (see Tables II, III, and VIII).

From the preceding paragraph, it is clear that the criterion of Table XIV, like that of Table XIII, has the shortcoming of not considering solutions quantitatively. How should quantitative results be reported?

## Accuracy/Optimality

Tabulating raw solution values as in Tables I through XII can give some quantitative indication of relative performance. However, the objective values have more meaning if they can be related to the optimal solutions. This is done by comparing them to the optimum, by bounding their percentage difference from the optimum, and by determining some minimum probability of their being in some very small best fraction of all solutions. Three tabulations are used to do this:
(1) Runs finding a known or suspected optimum (Table XV).
(2) Runs within certain percentages of a bound on the optimum (Table XVI).
(3) Runs giving solutions very likely to be in a very small best quantile of all solutions (Table XVII).

In some runs, the optimum was either known or suspected, usually based on comparison of the continuous optimum to the best heuristic solution. Examples of this can be seen in Table V (suspected optimum for $b_{i k}=740$ of 2503 where the continuous optimum was 2499.3) and Table VI (known optimum for $b_{i k}=790$ of 1963 , the next integer above the continuous optimum of 1962.2).

The entries in Table $X V$ are in the form $F / T(P \%):$

F: Number of known or suspected optima Found by a given method.

T: Total number of problems attempted by the method where the optimum was known or suspected.

P: Percentage of $T$ represented by $F$.
VAMI and VAMC gave identical results for this criterion, so their entries are combined in Table XV.

Clearly, the best results from this point of view were produced by VAMI/VAMC in finding every known or suspected optimum. This does not

TABLE XV

FREQUENCIES AND PERCENTAGES OF METHODS FINDING KNOWN OR SUSPECTED OPTIMAL SOLUTION

| Method | $\begin{gathered} \text { Problem } \\ \text { Size } \end{gathered}$ | Known Optimum |  | Suspected Optimum |  | Combined Results |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| RANDC | Large | 14/17 | (82\%) | 3/10 | (30\%) | 17/27 | (63\%) |
|  | Small | 9/9 | (100\%) | 18/18 | (100\%) | 27/27 | (100\%) |
| VAMI/ | Large | 17/17 | (100\%) | 10/10 | (100\%) | 27/27 | (100\%) |
| VAMC | Small | 9/9 | (100\%) | 18/18 | (100\%) | 27/27 | (100\%) |
| LPMAX | Large | $12 / 12$ | (100\%) | $4 / 7$ | (57\%) | 16/19 | (84\%) |
|  | Small | 2/6 | (33\%) | 12/12 | (100\%) | 14/18 | (78\%) |
| GREEDY | Smal1 | 7/7 | (100\%) | 9/14 | (64\%) | 16/21 | (76\%) |

TABLE XVI

CUMULATIVE FREQUENCIES AND PERCENTAGES OF RUNS WITHIN VARIOUS TOLERANCES OF THE BEST BOUND ON THE OPTIMUM

|  | Method |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | RANDC | VAMC | VAMI |  | LPMAX |  | GREEDY |  |
| Large Problems |  |  |  |  |  |  |  |  |
| Total Runs | 39 | 39 |  | 39 |  | 39 |  | None |
| 2\% | 16 (41\%) | 21 (54\%) | 29 | (74\%) | 15 | (38\%) |  | -- |
| 5\% | 25 (64\%) | 25 (64\%) | 33 | (85\%) | 16 | (41\%) |  | -- |
| 10\% | 27 (69\%) | 35 (90\%) | 37 | (95\%) | 23 | (58\%) |  | -- |
| 15\% | 29 (74\%) | 37 (95\%) | 37 | (95\%) | 27 | (69\%) |  | -- |
| Small Problems |  |  |  |  |  |  |  |  |
| Total Runs | 45 | 45 |  | 45 |  | 32 |  | 35 |
| 2\% | 22 (49\%) | 22 (49\%) | 22 | (49\%) | 12 | (38\%) | 14 | (40\%) |
| 5\% | 27 (60\%) | 27 (60\%) | 27 | (60\%) | 17 | (53\%) |  | (60\%) |
| 10\% | 27 (60\%) | 30 (67\%) |  | (67\%) |  | (53\%) |  | (60\%) |
| 15\% | 39 (89\%) | 42 (93\%) | 42 | (93\%) |  | (66\%) | 28 | (80\%) |

TABLE XVII
FREQUENCIES AND PERCENTAGES OF SOLUTIONS EQUALING OR EXCEEDING VALUES OBTAINED BY RANDR OR RANDC WITH LARGE VALUES OF N

| $\begin{gathered} \text { Problem } \\ \text { Size } \end{gathered}$ | Evaluation <br> Standard, N | RANDC |  | VAMC |  | VAMI |  | LPMAX |  | GREEDY |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Large | RANDR, 2000 | 15/17 | (88\%) | 15/17 | (88\%) | 17/17 | (100\%) | 17/17 | (100\%) | -- |
|  | RANDR, 500 | 22/24 | (92\%) | 24/24 | (100\%) | 24/24 | (100\%) | 18/24 | (75\%) | -- |
|  | RANDC, 2000 | 2/17 | (12\%) | 13/17 | (76\%) | 17/17 | (100\%) | 11/17 | (65\%) | -- |
|  | RANDC, 500 | 14/24 | (58\%) | 22/24 | (92\%) | 22/24 | (92\%) | 12/24 | (50\%) | -- |
| Small | RANDR, 2000 | 54/66 | (82\%) | 51/66 | (77\%) | 57/66 | (86\%) | 32/47 | (68\%) | 36/53 (68\%) |
|  | RANDC, 2000 | 54/66 | (82\%) | 48/66 | (73\%) | 51/66 | (77\%) | 23/47 | (49\%) | 34/53 (64\%) |

mean that VAMI/VAMC will always find the optimum. Problems for which the optimum is easily found are not at all typical, and VAMI/VAMC, as can be seen under $b_{i k}=1370$ in Table II, "must occasionally produce arbitrarily bad approximations," as noted in Chapter III, page 33.

Probably the most meaningful statistics for judging the relative capabilities of the methods in finding good solutions are given in Table XIV. For problems where feasible solutions were known to exist (usually because they were found by some heuristic), frequencies and percentages are tabulated to show how of ten each method produced a solution that was within (a) 2 percent, (b) 5 percent, (c) 10 percent, and (d) 15 percent of the greatest lower bound (usually the continuous optimum) on the optimal solution.

The frequencies and percentages in Table XIV are cumulative. For example, RANDC gave a solution within 20 percent of the best bound on 16 ( 41 percent) of 39 large problems, while 25 ( 64 percent) of 39 RANDC solutions were within 5 percent of the bound. This, of course, implies that 9 solutions from RANDC were between 2 percent and 5 percent greater than the bound.

The best results for large problems were again produced by VAMI, where 95 percent of all solutions to problems known to possess a feasible solution were within 10 percent of the optimal solution, and 85 percent were within 5 percent. For small problems, VAMI, VAMC, and RANDC did not differ significantly, although it should be noted that RANDC ranks behind VAMI/VAMC according to this criterion, which is the reverse of what was reported in Tables XIII and XIV. Again, this happens because solutions from VAMI that were superior to those from RANDC were sometimes very superior, but the reverse was seldom true. RANDC and

VAMI/VAMC also produced many identical solutions, especially with fairly loose constraints.

Another view of optimality is the statistical approach of Table XVII. McRoberts [20] pointed out that it is easy to calculate the number ( $N$ ) of equally likely solutions that must be randomly generated to have a specified confidence (C) that the best solution obtained will be within a given best fraction ( P ) of all solutions:

$$
1-\mathrm{C} \doteq(1-\mathrm{P})^{\mathrm{N}} \quad \text { so } \quad \mathrm{N} \doteq \frac{\log (1-\mathrm{C})}{\log (1-\mathrm{P})}
$$

$N$ must thus be 459 or more to be 99 percent confident of obtaining a solution from the 99th percentile ( $\quad(=.01$ ) of all solutions, and if $C$ $=.997$ and $P=.003, N=1944$. Tests were run using RANDR with $N=500$ or $\mathrm{N}=2000$.

Besides being convenient round numbers, 500 and 2000 are conservative, because they could actually be associated with larger values of $C$ and/or smaller values of $P$. Also, RANDR itself is conservatively biased because it will not assign an infeasible agent to any task, which makes most good solutions much more probable than most bad solutions.

Unfortunately, there are $\mathrm{m}^{\mathrm{n}}$ solutions to each problem. In a 50variable problem, $\mathrm{m}^{\mathrm{n}}$ is of the order of $10^{5}$ to $10^{7}$, so there are hundreds or thousands of solutions within the upper fraction $P$ of all solutions, even when $P=.003$. As can be seen from Tables II - VII, RANDR with $N=2000(C \doteq .997, ~ P \doteq .003)$ produces solutions that are usually worse than those found by the methods being evaluated. The situation deteriorates dramatically for larger problems. If mn $\doteq 1000$, $m^{n}$ will be of the order of $10^{50}$ or $10^{100}$, so enormous numbers of
solutions would be implied by the smallest fraction of all solutions associated with reasonable values of $C$ and $P$. The starkly inferior solutions to large problems produced by RANDR with $N=500$ or 2000 are evident in Tables VIII - XII.

RANDC, however, produces good solutions even for small values of $N$, as has been seen. RANDC is much more biased toward good solutions than RANDR, so running RANDC with a large $N$ should give great confidence of obtaining one of the very best solutions.

A drawback of RANDC, especially as an evaluation tool, is that it is biased against good solutions in some highly-constrained problems. The best coverage for such problems is often achieved by assigning many tasks to agents that are expensive, but especially resource-efficient. It is possible to devise examples where RANDC would never find an obvious optimum, because of its rule of assigning each task to the cheapest available agent. It is believed, however, that actual problems will rarely exhibit this difficulty.

Table XVII is useful despite the difficulties set out in the preceding paragraphs. It gives strong intuitive support to the contention that some methods are extremely likely to find one of the few very best solutions, even though the likelihood and quantile cannot be determined.

The entries in Table XVII are in the form $N / T(P \%):$
N: Number of runs giving a solution at least as good as: that found by the evaluation standard.

T: Total number of runs compared to the evaluation standard.
P: $N$ expressed as a Percentage of $T$.
VAMI again stands out for large problems. RANDC does well on1y for small problems, although it is certainly not "fair" to evaluate it
against an "advantaged" version of itself. VAMC does very well, considering that it requires so little time.

Although the objective value is severely penalized when the solution does not cover all tasks, there remains a need to test the ability of each method to find solutions covering as many tasks as possible. Coverage (Feasibility)

Table XVIII is intended to estimate the probability that a given method will find a solution covering all tasks, provided a continuous solution exists. The entries are frequencies and percentages from among 45 small problems and 39 large ones possessing continuous solutions. All methods find feasible solutions fairly reliably, but VAMI, with 100 percent success for both problem sizes, is clearly superior.

TABLE XVIII
FREQUENCIES AND PERCENTAGES OF FINDING FEASIBLE SOLUTION WHEN CONTINUOUS SOLUTION EXISTED

| Problem <br> Size | Number <br> of Runs | RANDC | VAMC | VAMI | LPMAX | GREEDY |
| :--- | :--- | :---: | :---: | :---: | :---: | :---: |
| Large | 39 | $37(95 \%)$ | $37(95 \%)$ | $39(100 \%)$ | $33(85 \%)$ | - |
| Sma11 | 45 | $42(93 \%)$ | $42(93 \%)$ | $45(100 \%)$ | $36(80 \%)$ | $39(87 \%)$ |

Up to now, the solution itself has been the only information from the test runs to be investigated. The computer time and storage
required to produce these solutions also need to be considered, especially since this research was motivated by a need to conserve these resouces.

## Response Time

The computers used for almost all this research were large, fast IBM 370-series systems. The CPU time required by these machines is only about a fourth of that needed by more typical equipment. Tables II through XII show the amount of CPU time required for one run using each method. For large problems, RANDC and VAMI/VAMC are clearly the only methods that can be counted on to provide response times suitable for conversational use on most computer systems. CPU times listed for LPMAX include the time required by MPS, but they do not include time for interfacing the three-step program sequence (MPSGEN, MPS, LPMAX), which admittedly can be refined beyond what was done here, but would always be costly. Requirements for data interface also plague LPMAX. RANDC and VAMI/VAMC generate all solutions in main storage, so CPU time is the only determinant of response time. However, the linear programming formulation of a large generalized assignment problem (mn variables; mp +n constraints; mn upper bounds) forces MPS (or whatever) to use peripheral storage, which lengthens response time considerably.

Execution (CPU) time was observed to be affected by problem size (mn), the number of resources ( p ), and problem shape ( $\mathrm{m} / \mathrm{n}$ ). It was impractical to make the number of runs necessary to investigate this thoroughly, so it was decided to place the most emphasis on effects that were unexpected or otherwise especially interesting.

## Problem Size (mn)

During preliminary testing, results were at first confusing until it was noted that execution time was affected by the shape as well as the size of the problems. Then, by holding $\mathrm{m} / \mathrm{n}$ relatively constant while varying mn, results were obtained that were quite as expected:
(1) For the construction heuristics, execution time was a linear function of mn. This is not surprising, since for each of $n$ tasks, a maximum of $m$ agents are considered by these methods, without any combinatorial complications between tasks. The MPS overhead for LPMAX also contributed linearly to execution time as mn increased, which is normal for linear programming algorithms.
(2) With improvement heuristics, however, execution time was a quadratic function of mn . This is to be expected since they consider assignments in pairs, and there are $0\left(m^{2} n^{2}\right)$ possible pairs.

## Number of Resources (p)

This was held constant (usually at 2,3 , or 4 ) while investigating the effect of problem size. When $p$ was varied under constant problem dimensions, effects were observed that were quite as expected:
(1) Execution times of RANDR, RANDC, and VAMI/VAMC did not change much. The time spent checking resources is small compared to the time spent seeking minima in columns, calculating penalties, etc.
(2) LPMAX (actually the MPS phase) was strongly affected. Adding one to $p$ increases the number of constraints by $m$. This means that the CPU time required by an improvement heuristic will therefore be multiplied by a factor of about $p$ to become $0\left(m^{2} n^{2} p\right)$.

Problem Shape (m/n)

The most interesting results were produced by varying this factor.

Unlike the factors discussed above, problem shape affects the fast
methods RANDC and VAMI/VAMC, but it has little effect on other methods. The most interesting thing about problem shape is that it affects execution time of RANDC in a way opposite to the effect on VAMI. These opposite effects are graphed in Figures 11 and 12.

Why is VAMI slower for "wide" or "tall" problems than for "square" ones? For "wide" problems, recalculation of penalties must be done for more tasks than with other shapes. As problems become "tall," the search for the two smallest elements in a column begins to require more time.

The reason why RANDC is slowest for "square" problems is less obvious. RANDC uses time for choosing the next task to optimize, and for finding the cheapest available agent. Fewer tasks must be chosen in a "tall" problem, but finding the cheapest agent takes less time in a "wide" problem. Apparently the combined effect is worst for "square" problems.

## Storage Requirements

All the methods were well within the capacity of a fairly small computer, except LPMAX. The MPS package requires far more storage (about $2,000,000$ bits) than a user-written routine for the continuous solution, but the latter would still be very large and costly to develop.

As will be seen in Chapter $V$, it is possible to sharply reduce the amount of storage used by packing two or more numbers into the space normally used for one, at a slight cost in execution time. However, most users will have sufficient storage available to avoid packing. Under the assumption that each numeric value uses one "word" of storage, the various methods require array storage as follows:


Figure 11. Effect of Shape on Average CPU Time Required for One RANDC Solution


Figure 12. Effect of Shape on CPU Time Required for 11 VAMI Solutions

Storage Words

RANDR $\quad(p+1)(n+1)(m)+n$
RANDC, LPMAX $\quad(p+1)(n+1)(m)+2 n$
VAMC $\quad(p+1)(n+1)(m)+3 n$
VAMI

Increment

n
n
$2 m n$

The storage requirement for LPMAX does not include the overhead of MPS. The above requirements can be halved with many computers by using half-word integer storage.

The methods require storage for the program logic, also. This will differ between computers, but the implementations in Appendix A used program storage (for subroutine SOLVER, less array storage) in the following approximate amounts (in bits):
RANDR 24000

RANDC 25000
LPMAX 26000
GREEDY / CRAFTY 35000
VAMI/VAMC 40000

For a fairly large problem $(m=100, n=15, p=4)$, it should be possible to implement VAMI in 200,000 to 500,000 bits of storage, depending on word length, which is well within the capacity of almost any computer. RANDC would require slightly more than half as much storage as VAMI.

Summary

It is clear that RANDC and VAMI/VAMC are superior to the other methods, but the conclusions and recommendations to be drawn from the results presented in this chapter will be developed in Chapter VI, after Chapter V describes two implementations.

CHAPTER V

TWO IMPLEMENTATIONS

Introduction

The methods described in Chapter III must be modified to fit most applications. This is due to constraints of the solution environment as well as complications of the problem itself. This chapter describes ways of dealing with (a) an environmental constraint (limited computer resources), and (b) a complicated problem (the artillery problem of Figures 3 through 5).

## Limited Computer Resources

## Background

Until recently, the size and cost of computers made them impractical for many on-the-job applications. Almost overnight, miniaturized equipment that is startingly sophisticated has become available at about the same cost as an electric typewriter or a forklift truck. Computers can now be located in industrial environments where assignment problems are encountered. Deciding which machine or worker does which job need no longer be a haphazard process. There is great potential here for improved productivity. Most of the methods described in this dissertation can be used with microcomputers, especially RANDC and VAMI. This section, adapted from Thibault et al. [32], shows how
machines are assigned to jobs in an operational situation. The discussion will be in terms of "machines" and "jobs" instead of agents and tasks. Two resources will be considered: "material" and "time."

## Simplifications in Methods

The logic of RANDC remains essentially unchanged. VAMI considers only five " $Q$ " values ( $0,0.1,0.2,0.4,0.8$ ), and calculates penalties only for the two lowest-cost machines for each job, with no penalties being recalculated during the solution process.

## Simplifications in Problem Data

Besides allowing for only two resources, it is assumed that costs and resource requirements can be predefined as part of the program, since the set of machines and the set of possible jobs, along with the corresponding cost and resource data, usually do not change often. The items that change frequently are:
(1) Which machines or jobs are to be considered from the set of those possible, and
(2) The available supplies of material and time.

This is the only information the user must specify. (RANDC also requires a random number seed and the sample size.)

The user-specified subsets of cost/resource data are moved into the "northwest corner" of the corresponding main arrays before the solution phase of the program begins.

## Saving Time and Storage

The use of predefined data allows the further simplification of
using presorted and pre-indexed costs. The machine indexes and the costs are packed (to save storage) in the form ccccii, where cccc indicates the cost and ii the index. These indexed costs are presorted by the user into descending order for each task. They are part of the source program. This simplifies and speeds up both RANDC and VAMI by making it very easy to find the "next cheapest machine" for a given job.

Similarly, requirements for material and time are packed (mmmttt), but they are entered for each job in the order in which machines are numbers.

Of course, using predefined data may not always be appropriate. Programs can easily be coded to read costs and resource requirements, but they are rather error-prone and tedious to use for problems of realistic size.

For example, suppose job two's costs and resource requirements were as shown in Table XIX. The data for job 2 would be entered in the source program as follows. (Note that leading zeros are not necessary and that $\% *$ is entered as a cost of 9999 with material and time requirement of zero.)

1080 REM JOB 2
1090 DATA 4804,5060,6303,6805,8701,9607,999902
1100 DATA 16016,0,28062,38089,12069,96019,50033
The packing techniques require only six-digit precision. (Costs and resource requirements must be scaled if necessary.)

## Programs

Appendix C contains sample programs written in a subset of BASIC that will work on most microcomputers. Identical code (through statement
1970) is used in all programs to initialize and acquire all data except the special items needed by RANDC. The solution routines are as alike as possible, given their differing logic.

TABLE XIX
EXAMPLE OF DATA TO BE ENTERED IN MICROCOMPUTER PROGRAM

|  | Machine No. |  |  |  |  |  |  |  |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | :---: |
|  | 1 | 2 | 3 | 4 | 5 | 6 | 7 |  |
| Cost | 87 | $* *$ | 63 | 48 | 68 | 56 | 95 |  |
| Material | 16 | $* *$ | 28 | 38 | 12 | 95 | 50 |  |
| Time | 16 | $* *$ | 62 | 89 | 69 | 19 | 33 |  |

** Means that the job cannot be done on the corresponding machine.

Program Outputs

As can be seen from the examples in Appendix D, both programs give the user an opportunity after completion (NEW RUN?) to either restart completely (YES) or try some other set of resource supplies (RHS -- for "Right-Hand-Side"). Before completion, RANDC asks if the user wants additional trials to be made (MORE TRIALS?). If YES is input, RANDC asks HOW MANY?

The program output is otherwise largely self-explanatory, except for the following hotes:
(1) The total cost of a solution will be printed with one asterisk to the left of the word COST for each job remaining unassigned to any machine. This, in addition to the listing of UNASSIGNED JOBS, is designed to alert the user that a particular solution is incomplete (which may be a natural result of limited supplies of resources).
(2) Slack data are printed to help guide the user to a successful reallocation of resource supplies. However, the mathematical properties of this problem can make reallocation a tricky process.
(3) Both programs occasionally produce duplicate solutions in an effort to provide the user with multiple alternatives.

Testing and Evaluations

RANDC and VAMI were run against 180 randomly generated problems as indicated in Table XX. RANDC was allowed ten trials to the five (one for each Q) allowed to VAMI, because it was estimated to take about twice as long to generate penalties as random numbers. Ten different sets of dimensions were used, varying from $6 \times 3$ to $3 \times 10$ to represent most problem "shapes" that would be possible in the $7 \times 10$ program arrays. For each set of dimensions, three different sets ("Problems 1, 2, and 3") of cost and resource coefficients were used. For each of these, tight, medium, and loose ("T, M, and L") resource supplies were tried. In Tab1e XX, the method performing best for a given problem is denoted by " R " for RANDC and " $V$ " for VAMI with "-" indicating a tie.

It is clear from Table XX that there is no significant difference between RANDC and VAMI for a basic problem. RANDC can be easily run for a very large number of trials to obtain a more realiable estimate of the true optimum, and it is much easier to understand and explain than VAMI. However, VAMI does have certain advantages if many complications are present," as will be seen.

## TABLE XX

SUMMARY OF TEST RESULTS FOR MICROCOMPUTER IMPLEMENTATION

| Dimensions | Problem 1 |  |  | Problem 2 |  |  | Problem 3 |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | T | M | L | T | M | L | T | M | L |
| 6x3 | - | V | - | - | - | - | - | - | - |
| $7 \times 4$ | - | - | - | - | - | - | - | R | - |
| 3x3 | - | - | - | - | - | - | V | V | - |
| $5 \times 5$ | - | - | - | R | R | - | R | - | - |
| $7 \times 7$ | - | - | - | R | R | - | R | - | - |
| $3 \times 5$ | R | R | - | - | - | - | R | V | - |
| $5 \times 8$ | R | R | - | R | - | - | R | V | - |
| $7 \times 10$ | R | R | - | R | - | R | R | V | V |
| 2x6 | R | - | - | - | R | - | - | - | - |
| $3 \times 10$ | V | V | - | V | R | - | R | V | - |

## Complications in General

Complications make the task of optimizing a job much more difficult. However, VAMI-type penalties can still usually be calculated in a straightforward way, so the extra time they take diminishes in importance, because the process of optimizing a job may take much longer than choosing a job to optimize. Thus, requiring fewer trials than RANDC can be a big advantage. Below are ideas for dealing with specific complications, mostly adapted from the artillery problem.

Job Priorities. As suggested in Chapter II, each group of jobs of a given priority could be treated as a separate subproblem, solved in order of decreasing importance. VAMI (or RANDC, if this is the only complication) is suitable for this. Another way would be to transform the costs for job $j$ according to priority (being careful to ensure highest costs and penalties for the most important jobs) before solving with VAMI ro RANDC.

Alternative Resources. A good example of this complication is the availability of several types of ammunition to an artillery unit. This can be handled by defining a group of multiple machines, one for each alternative resource, and assigning as usual, decrementing time for all "machines" in the group.

Shared Jobs. Sophisticated approaches are very difficult to fit into a microcomputer, but it may be possible to specify a fictitious mmachine, representing two or more others in combination, and decrementing resources for all machines involved in the assignment. This complication does not combine well with alternative resources. Such a
combination might best be handled with VAMI.

Multiple Objectives. If this is the only complications, RANDC with modified objective evaluation is probably best. Otherwise, VAMI is likely to be better, if the penalty calculations are based on the multiple objectives.

## Notation

BASIC severely limits variable names, so the code in Appendix C is not the same as that used in Appendix A. Table XXI establishes notational correspondence between Figure 7, Appendix A, and Appendix C for important variables with different names.

The Artillery Problem

## Introduction

The basic solution approach descends directly from VAMI. Targets are optimized in a sequence based on penalties calculated from weighted combinations of costs and resource inefficiencies. Optimizing a target is a very complicated process, however. Also, extreme measures were taken to save time and storage while allowing the use of variable problem dimensions ( $m$ and $n$ ) without recompiling the program. This makes the program (Appendix E) almost indecipherable, in spite of detailed documentation with comment cards.

It is most unlikely that the program of Appendix E could be used in another application without extensive modification. The following Summary Flowchart and Narrative Outline of the Solution Routine present the procedure in a form that is easier to understand and more likely to

TABLE XXI

NOTATION IN APPENDIX C

| Name in Appendix C | Contents | $\begin{gathered} \text { Appendix } \\ \text { A } \end{gathered}$ | $\underset{7}{\text { Figure }}$ |
| :---: | :---: | :---: | :---: |
| A | Assignment vector | XB | X |
| B, T | Initial resource supplies | IB | b |
| C5 | Current objective function value | Z | Z |
| G1 | Best objective function value yet found | MINZ | $\mathrm{Z}_{\text {min }}$ |
| L | Index of task currently being optimized | JBIG | J |
| M7, N7 | Maximum array dimensions | - | - |
| P | RANDC: vector for shuffling task indices | T |  |
|  | VAMI: vector of task penalties | H | H |
| R | Packed resource coefficients | A | a |
| R9 | RANDC: Random number seed | ISEED | d |
| U, V | (a) temporary storage for moving cost and resource data into "northwest" corners of main arrays | - | - |
|  | (b) amounts of resources remaining | B | B |
| U6 | Count of tasks that could not be assigned | U | u |
| $Y$ | Indices of user-specified subset of agents | - | - |
| Z | (a) indices of user-specified subset of tasks | - | - |
|  | (b) RANDC: number of trials (BASIC arrays and scalars can share a name) | NBIGQS | N |

provide inspiration. (Appendix $F$ contains an output example for a small problem.)

## Summary Flowchart

After the "Input Phase" is complete, a "Control Routine" supervises the generation and printing of solutions by the "Solution Routine" and the "Output Routine." The overall logic of this process is given in the Summary Flowchart in Figure 13.

Table XXI refers to a "P-matrix" and "Q." These items are similar to those of the same names used in VAMI.

In interpreting Figure 13, it should be noted that the "Output Routine" is designed to produce different lists (emulating video outputs), depending on the codes passed to it by the "Control Routine" and the "Solution Routine."

## Narrative Outline of the Solution Routine

I. For each target priority class:
A. Obtain penalties for each target in priority class. Penalties depend on number of units desired (one for normal assignment, more for mixed assignment) versus number of units available.

1. No units available: Penalty is -1 (lower than any other penalty) because nothing can be gained by making an early assignment.
2. Number desired exceeds number available: Penalty is $500,000+100,000 \times$ (shortage).
3. Number desired equals number available: Penalty is 500,000 .
4. Number desired is one less than number available: Penalty is $100,000+$ largest difference between two successive (in size) P-matrix values for target.


Figure 13. Summary Flowchart for Solution of Artillery Problem
5. Otherwise: Find, from each unit, the type of ammunition having the lowest $P$-value for this target. Penalty is the greatest difference between two such values over all units.
B. Optimize targets in order of highest-to-lowest penalties. Logic depends on whether mixed assignment and/or start/stop times are specified. (Note: "cheapest" as used below means having smallest P-value for a given target.)

1. Unmixed assignments with start/stop times specified: Make cheapest feasible assignment that fits start/ stop period. If only start (or only stop) specified calculate other end of firing period as specified in $5-4 a$ and $5-4 b$ of Figure 5 .
2. Unmixed assignments with no start or stop time: Make cheapest feasible assignment, starting as early as possible in the unit's shortest satisfactory schedule gap.
3. Mixed assignment: Calculate "Mixing Limits" as the maximum (TMASMX in Appendix E) and minimum (TMASMN) over all units of the time required for each unit to cover its "ideal share" of a mixed assignment. This "ideal share time" is the amount of time the unit would need to fire a number of shells that would be the smallest integer not exceeded by $a_{i j k} / M_{j}$ (see Figure 5).
a. Both start and stop times specified:
(1) Check every unit (in order of ascending $P$ value for this target) to determine if the unit's ammunition supply and schedule permit it to contribute anything to the coverage of this target. If so, add it to list of prospective mixed assignment participants.
(a) If desired number (or more) of units is in list, check if coverage is complete. If it is, go assign. Otherwise, check next unit.
(b) If no more units are available and coverage is complete, go assign. If coverage is not complete, target remains unassigned.
b. Start or stop time (not both) specified:
(1) Determine the set of units able to fire at least one volley. From all such units find the maximum (AVAMAX) and minimum (AVAMIN) length of a schedule gap bounded on one end by the specified start or stop time.
(2) Try to fit mixed assignments in the following order of length: TMASMX, TMASMN, AVAMAX, AVAMIN. Exclude cases known in advance not to fit, e.g., when TMASMX is greater than AVAMAX. The procedure for trying to fit each of these trial lengths is similar to that used when both start and stop times are specified. If complete coverage cannot be achieved with one trial length, then try the next, but assign as soon as any possibility for complete coverage is found. If no trial length gives full coverage, target remains unassigned.
(3) If possible, shorten the successful trial length until at least one participating unit has only exactly enough time for its share. Then assign.
c. Neither start nor stop time specified:
(1) Determine set of trial lengths to be specified according to TMASMX minus TMASMN:

(2) Scan schedules of units, starting with cheapest, looking for gaps. Each time a gap is found, try to fit a mixed assignment of the current trial length in it. If scan produces a gap suitable for a "perfect mixed assignment" (number of participating units exactly as specified; each unit can cover a "perfect share"), assign immediately after attempting to shorten length as in I.B.3.b. (3) above. Otherwise, save best gap yet found.
(3) If no "perfect mixed assignment" is found for the current trial length, start scanning again for next trial length.
(4) If no trial length produces a "perfect mixed assignment," check the best gap yet found. If full coverage is not possible in that gap, target remains unassigned. Otherwise, assign target in this "best gap," attempting to shorten length as in I.B.3.b.(3).
C. "Assigning" means adding elements to scheduling arrays, updating counters and pointers, decrementing ammunition supplies, etc. Also, an output routine is called to print a summary of the assignment for this target on the "Target Assignment List."

## Interpreting Appendix E

The notation of Appendix E does not correspond exactly to Figures 3 through 5. There are two main reasons for this:
(1) The program, typical of many heuristics, does not operate on the model explicitly. There are elements in the program that are not present in the model, and vice versa.
(2) The sponsor of the research preferred that notation developed in preliminary research be continued.

Also, Appendices E and F refer to "massed fire," etc. instead of "mixed assignments." This was again a sponsor preference.

The Narrative Outline mentions discretionary resources only once. This is because each unit is broken up into several fictitious units (one for each ammunition type). Thus, the term "unit" actually can be read as "row," or "distinct ammunition/unit combination." When an assignment is made, the schedules and remaining time supplies are, of course, updated for all rows associated with the assigned unit.

Appendix E also deals with "primary" and "secondary" rows. The user has the option of specifying a set of rows that receive primary consideration for assignment to a given target. The secondary rows are those specified for consideration if sufficient primary rows are unavailable. This is handled by treating the primary rows as though
they were "cheaper" than the secondary rows.

Interpreting Appendix F

These lists are designed to be self-explanatory. The term "ALPHA" is used for " $Q$ " because of the sponsor preference noted above.

The solution routine is intended for use in a conversational environment. Appendix F can therefore be seen as data that will eventually be kept in peripheral storage and displayed on a screen as needed, instead of being printed immediately after generation.

Testing and Evaluation

The user supplied only one set of problem data for test purposes. The problem was too large (37 rows, 27 targets) for initial debugging. Output from this problem is not included in this dissertation for these reasons:
(1) The problem contained logical conflicts that prevent any feasible solution from being found.
(2) No basis has been established by the user for evaluating the objective function. The procedure for determining cost coefficients is currently under revision. The form of the objective function has not been fixed.
(3) The current Appendix F is less cumbersome to use but does not omit any important information.

A few smaller problems were randomly generated and used in debugging the program code, but no formal testing was done, since the objective function remains undefined. However, even for the $37 \times 27$ problem, the program ran quickly enough for conversational use, and the answers that were obtained appeared to satisfy well the admittedly hazy objective criteria of Figure 3, given any unremovable infeasibility. Also, program size was such that the user could expect to implement the
application in 500,000 bits of storage.

## Conclusions

This application points up the adaptability of VAMI. RANDC (for an $N$ of reasonable size) would have required too much time because of the complex process of optimizing a target. It is difficult to imagine any way to implement LPMAX. GREEDY and CRAFTY use too much time for smaller and much simpler problems. VAMI, however, is again a standout, as was so often seen in Chapter IV.

## CHAPTER VI

SUMMARY, CONCLUSIONS, CONTRIBUTIONS, AND RECOMMENDATIONS

Summary

## The Problem

Multi-resource generalized assignment problems have been identified in many applications. Unfortunately, these problems are very difficult to solve, especially if complications are present.

## Optimal Solutions Unavailable

Apparently, no cost-effective optimal solution method can be developed. Optimal methods also have several disadvantages per se:
(1) They are difficult to adapt to changing requirements.
(2) They do not produce several solution alternatives.
(3) They use much storage and computer time, which is usually unjustified, since data are often inexact.

## Heuristic Approaches

This research has produced several heuristic solution methods. Construction heuristics use various forms of logic to build a solution from the problem data. These forms of logic, along with the corresponding heuristics developed in this research, are:
(1) Random (RANDR, RANDC)
(2) Penalty-Guided (VAMI/VAMC)
(3) Adjusted Continuous Solution (LPMAX)

Improvement heuristics try to make an existing solution better. GREEDY and CRAFTY do this by switching the assignment of two tasks to different agents.

Objectives

This research has sought methods for realistic aspirations for:
(1) Quantitative performance measures: Task coverage, response time, accuracy/optimality, computer storage.
(2) Qualitative performance measures: Adaptability, alternate solutions, ease of use, predictability of response time.

## Testing

The methods have been programmed and tested on a number of problems. A number of criteria were used to compare the relative performances of the heuristics. Distinct differences in performance were observed, along with some interesting characteristics of individual methods.

Implementations

Two demonstrations have been developed of implementations under extreme circumstances:
(1) Limited computer resources
(2) Extremely complicated problem

Results have been fairly satisfactory, so far as interpretation is possible.

Conclusions

Evaluation of Test Results

Each of the objectives of this research will be considered to determine:
(1) whether it was achieved, and
(2) which method(s) performed best in achieving it. Additionally, a tabulation is made of conclusions about the performance of individual methods in achieving research objectives.

## Realistic Problems

Chapter V makes it clear that the basic methods VAMI and, to a lesser extent, RANDC can be adapted to fit a variety of realistic problem situations.

## Coverage

The aspiration level given in Chapter $I$ was to find a solution covering all tasks in 90 percent of ". . . the cases tested." It is only reasonable to add the qualification that the continuous solution must exist, since there can be no full coverage otherwise. Table XVIII shows that VAMI, VAMC, and RANDC exceeded this level (VAMI scored 100 percent!), with both LPMAX and GREEDY at or above 80 percent. For the 28 problems where full coverage was apparently impossible, only three cases were encountered where VAMI failed to cover as many tasks as believed possible.

The aspiration level of five minutes can be guaranteed for large problems only by RANDC and VAMI/VAMC. One might reduce the value of $N$ or $q$ to speed up these methods, if an increased chance of a bad solution could be tolerated.

Interesting effects on the response times of RANDC and VAMI/VAMC were observed to be caused by changing the "shape" of a problem of a given size. Qualitative considerations of response time also involved "shape," as will be seen.

## Accuracy/Optimality

Given existence of a feasible solution and knowledge of a bound on the optimum, the objective was to find a solution within 15 percent of the bound in 90 percent of the cases tested. VAMI/VAMC was the only heuristic to satisfy this criterion. Indeed, for large problems, VAMI was within 10 percent of the bound in 95 percent of the test runs! This result is even more remarkable if it is noted that the bound was usually the continuous optimum. There is, of course, no guarantee that the continuous optimum is anywhere near the actual zero-one optimum.

Consistent with the findings of Sahni and Gonzelez [28], every method occasionally produced terrible results. The probability of this could be substantially reduced by using two different methods on the same problem, provided the outcomes of the methods were very nearly independent.

It is debatable whether bad outcomes of VAMC and RANDC are independent events, since the probability that such events will occur simultaneously appears to be greater than the product of their individual
probabilities of occurrence. VAMC and RANDC both optimize a task in the same way and are thus both likely to miss good solutions in problems where that strategy is a poor one. This may have occurred in the results reported in the leftmost data columns of Tables VIII and IX.

VAMI may produce results more nearly independent of the outcome of RANDC, since VAMI was designed specifically to avoid the problem just described. However, it may well be that another set of problems exists where VAMI and RANDC do not produce bad answers independently. Not enough runs were made in this research to thoroughly investigate this proposition empirically. However, on only one test run (see Table II) did both RANDC and VAMI fail to find an appealing solution. This gives some intuitive support to the contention that the probability of such an event is very small indeed.

In summary, the following conclusion can be drawn regarding accuracy/optimality:
(1) VAMI is very powerful, often where other methods fail.
(2) RANDC is a useful supplement to VAMI.

Computer Storage

A11 the methods except LPMAX use less than half the amount of storage aspired to. There are ways of reducing storage requirements still further, however. Happily, the greatest reductions can be realized with VAMI, which uses more storage than other methods. Besides the use of halfword storage described in Chapter IV and the packing technique of Chapter V, VAMI can be programmed to store the cost and inefficiency matrices on a direct-access storage device. They would be needed only at the beginning of the process of generating a new
solution. Each recall would require only a fraction of a second, so the response time would probably suffer little. Direct-access devices are widely available even for microcomputers.

While this research was being done, developments in computer technology have made the consideration of storage much less vital. However, it remains comforting to conclude that heuristics are available that will enable almost any computer to be used on generalized assignment problems with an excellent chance of success.

Qualitative Criteria

As has been noted, VAMI is the most adaptable method, chiefly because its intermediate logic is not executed as often as that of other methods, and thus can be extensively redefined without costing much time. RANDC, however, is also quite adaptable, as long as the process of optimizing a task does not become too complicated.

All methods except VAMC produce multiple solution alternatives by design. RANDC and RANDR obviously offer more variety than other methods, although it is not clear that this is significant.

All methods are sufficiently easy to implement, operate, and maintain. It is estimated that one week or less would be required to implement any of the basic methods. Operation requires only that basic problem data be available. This could be generated by some automated process, or predefined, or at worst, keypunched. VAMI, the most complicated method to implement, might, in the long run, be the easiest to maintain in the face of changing requirements because of its
aforementioned flexibility. However, RANDR and RANDC would allow simple changes to be made readily. GREEDY/CRAFTY and LPMAX do not appear
to be robust with respect to changes; an apparently minor change in the problem definition might mean that the method would become useless (which is true, to some extent, of all methods).

As pointed out in Chapter IV, response times of RANDC and VAMI were a function of problem "shape" as well as size. The following expressions give highly approximate estimates of the CPU time in seconds required by RANDC and VAMI to produce one solution on the CDCmodified IBM 370-155-II at the University of Arkansas:

RANDC: $(\mathrm{Nmn} / 1000)\left(.2-.1\left(\log _{10}(\mathrm{~m} / \mathrm{n})\right)^{2}\right)$
VAMI: $\quad(\mathrm{Nmn} / 1000)\left(1+1.5\left(\log _{10}(\mathrm{~m} / \mathrm{n})\right)^{2}\right)$
The actual CPU time requirements are pseudorandom variables. Response time depends not only on CPU time but also on other parameters of the solution environment. Nevertheless, on most systems, response times of RANDC and VAMI will probably be:
(1) A linear function of mn , and
(2) An approximately quadratic function of $m$ for a given mn. These relationships should hold well enough for most planning purposes.

## Performance of Individual Methods

The conclusions drawn above are ordered by objective, which makes it difficult to extract information regarding the overall performance of each method. Also, some less important conclusions have not been mentioned. Therefore, all conclusions have been tabulated in Table XXII.

Table XXII leaves little doubt that VAMI is far superior to the other methods. VAMI is the only method that could conceivably be regarded as an all-round problem solver. No other method achieved all

TABLE XXII

TABULATED PERFORMANCE OF BASIC METHODS IN ACHIEVING OBJECTIVES

| Objectives | Method |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | VAMI |  | RANDC |  | VAMC |  | LPMAX |  | $\frac{\text { GREEDY }}{\text { S }}$ |
|  | L | S | L | S | L | S | L | S |  |
| Realistic Problems | * | * | M | M | * | * | U | U | U |
| Coverage | * | * | S | S | S | S | U | U | U |
| Response Time | S | S | S | S | * | * | U | U | S |
| Accuracy/Optimality | * | S | U | S | S | S | U | U | U |
| Adaptability | * | * | M | M | * | * | U | U | U |
| Multiple Solutions | S | S | * | * | U | U | S | S | S |
| Implementation | S | S | * | * | S | S | M | M | M |
| Operation | S | S | S | S | S | S | M | M | M |
| Maintenance | S | S | S | S | S | S | M | M | M |
| Predictable Time | S | S | S | S | S | S | S | S | U |
| * $=$ Outstanding |  |  |  |  |  |  |  |  |  |
| S = Satisfactory |  |  |  |  |  |  |  |  |  |
| $\mathrm{M}=$ Marginal |  |  |  |  |  |  |  |  |  |
| $\mathrm{U}=$ Unsatisfactory |  |  |  |  |  |  |  |  |  |

research objectives.
In spite of its failure to achieve all research objectives, RANDC does perform very well. It has advantages in areas not addressed by the research objectives:
(1) RANDC resembles the approach a decision-maker would be likely to devise. Therefore it is easy to explain, and has considerable ("infinite-number-of-monkeys") intuitive appeal.
(2) RANDC can make good use of additional computer time to increase the probability that it will find a good solution.
(3) Its results seem likely to be almost independent of those of VAMI, thus enabling the use of a powerful combination for especially intractable problems.

VAMC, although tested here as a special case of VAMI, could be implemented on its own if, for instance, it were known that constraints would never be particularly tight, but that rapid response time and minimal computer storage requirements were very important. Also, VAMI is not difficult to convert to VAMI, should the need arise.

LPMAX, GREEDY, and CRAFTY are not at all cost-effective, although LPMAX's by-product of a tight bound on the optimum and an index of constraint tightness are certainly useful for evaluating other methods. As will be seen under Recommendations, it even appears to be possible to improve performance of GREEDY and CRAFTY.

Contributions

## Introduction

This research has made several contributions. The most important of these was the development of powerful heuristic solution methods, but other valuable contributions include problem identification and definition, development of evaluation methodology, and demonstration
of specific applications.

## Heuristic Methods

All of these were inspired to some degree by one or more existing solution techniques. However, the ultimate development of the heuristics required two main creative inputs:
(1) Combination of techniques used with apparently unrelated classes of problems.
(2) Modification and extension of such techniques to fit the special structure of generalized assignment problems.

The process can be compared to the development of the rotary lawn mower from the previously known principles of scissors and the wheel.

VAMI is the outstanding example of this process of combination and modification. The Vogel Approximation Method (VAM) was combined with the LaGrangian approach of appending weighted resource considerations to the objective function. Modifications included the use of discrete values of $Q$ in place of the continuous-valued LaGrange multiplier, while only columns were optimized, instead of rows and columns as in the original VAM. Further modifications to fit extreme circumstances were described in Chapter V.

## Problem Identification and Definition

This contribution had to be made in order to justify this research. The most important aspect was recognition of the need to give explicit consideration to multiple resources in formulating models and devising solution methods. A further contribution in this category was the identification of the need to develop heuristic methods, not only because of the probable unavailability of optimal methods, but also
because of inherent disadvantages of optimal methods. Finally, as is evident in the artillery problem and elsewhere, assignment problems and scheduling problems often need to be solved simultaneously. The usual approach of first making assignments and then scheduling their execution is not always satisfactory.

## Evaluation Methodology

Many ideas were taken from the literature. Some, such as the pairwise comparison of methods using the nonparametric sign test [23], were changed little. Others, e.g. the use of long runs of RANDC to obtain an evaluation standard, were developed independently. Some traditional methodology (using the continuous optimum as a bound on the zero-one optimum) was, however, much more complicated to develop. Finally, using the $\not \equiv \mathrm{x}_{\mathrm{ij}}=1 / \not / \mathrm{x}_{\mathrm{ij}} \neq 0$ ratio ( $\mathrm{x}_{\mathrm{ij}}$ from the continuous solution) as an index of constraint tightness was an idea that occurred spontaneously during the development of LPMAX, but did not require any developmental work.

Whatever the source, the evaluation methodology used in this dissertation is more comprehensive than any that could be found in the literature. Accepting the reservation of Glover et al. [14] that there can be no "fair" evaluation standards, Chapter IV of this dissertation is likely to be one of the more comprehensive available sources of techniques for evaluating many types of heuristics.

## Realistic Applications

A researcher who is faced with a realistic problem will probably be unable to apply one of the methods of this dissertation without
modification. It is, of course, impossible for this research to examine every plausible variation that might occur. However, it is hoped that the researcher can be helped by the demonstrations and guidelines that are given in Chapter $V$ for handing extreme but dissimilar requirements.

## Recommendations

## Introduction

This section makes recommendations for using and explaining the heuristics developed in this research and for further avenues of research to pursue, specifically as regards development of better heuristics.

## Using the Heuristics

It would be a mistake to discard all methods except VAMI. There are situations where the use of VAMI would be inadvisable. RANDC is simpler and quicker to implement, and would probably be the method of choice if only a few loosely-constrained problems were to be solved, especially if the problems were not especially large. The advantage of RANDC's tendency to produce results independent of those of VAMI has already been noted. Again, VAMC might be best if speed were important and either constraints were loose or an occasional poor solution could be tolerated.

In conjunction with applications, some experience has been gained with explaining VAMI. It is crucial for the user to understand the method being used, because even such a powerful method may be otherwise rejected, perhaps covertly. The best reception has been given an approach that roughly parallels the development of VAMI:
(1) Description of an unsuccessful method, usually optimization of tasks in order from 1 to $n$.
(2) Discussion of the need to find a better-than-sequential order in which to optimize tasks.
(3) Introduction of the penalty concept and description of VAMC.
(4) Introduction of a simple example where VAMC fails because it does not adequately consider resources.
(5) Discussion of the concept of a "resource cost," or "resource inefficiency."
(6) Introduction of the combination of costs and inefficiency. It is not usually advisable to explain the concept of variable combining weight in great detail, since it is difficult to handle questions about predicting an "optimal" Q.

As an alternative, one might begin by explaining the concept of VAMC, and then discussing the incorporation of resource inefficiency as a cost, but in far less detail than suggested above.

Explanations of any method should be done in terms of the simple examples using small tables of numbers. Jargon such as "objective function" or "decision variable" should be regarded as taboo except with entirely academic audiences.

## Further Research

One glaring need for further investigation is certainly to test the heuristics with actual problems. Some preliminary research was done with hypothetical artillery data displaying highly nonrandom characteristics such as many equal or nearly equal cost or resource coefficients in a column or row. Results were too sketchy to interpret properly, but such problems may be more difficult than those used in this research. Tests in further realistic applications are likewise desirable as a means of revealing more about general applicability of the various
methods. There may be situations in which VAMI/VAMC is much less adaptable than some other method. Indeed, further testing per se is needed, both using problem sizes not considered in Chapter IV, and attempting to duplicate the results of this dissertation, especially using different computers.

Development and refinement of evaluation methodology would contribute not only to research with this class of problems, but also with heuristics in general. No claim is made that this dissertation is the last word on such methodology.

Next, it should be possible to refine the heuristic methods themselves. A preliminary attempt to improve the execution speed of GREEDY and CRAFTY appears to have chances of success. The modification used was to attempt to swap the two agents already assigned to a pair of tasks, instead of trying all possible new ways of assigning the tasks.

Perhaps RANDC should be slightly biased toward assigning the second cheapest agent to the task being optimized when constraints are tight. Alternatively, RANDC could be made to consider resource inefficiency in some way. Both ideas are attempts to suggest a way for RANDC to find good solutions to problems where assigning the cheapest agent is a poor strategy for optimizing a column.

Even VAMI may be subject to improvement. It may, for instance, be possible to avoid the time-consuming process of recomputing penalties by considering in penalty calculation the third-smallest element in the column. Also, it may be possible to get better results by not considering inefficiencies where an agent is well-supplied with resources. This technique would also increase execution speed.

LPMAX might give better results if it were guided in some way by
the dual variables from the continuous solution. Sensitivity analysis of the continuous solution can give information about the consequences of elevating some variables to one and reducing others to zero.

A11 construction heuristics make one assignment at a time. It certainly would seem worthwhile to investigate the usefulness of making two or more assignments at a time. The generalized form of this approach is to divide the overall problem into subproblems (sets of tasks) to be solved optimally or heuristically in some sequence. Defining and sequencing subproblems was done on the basis of task priorities in Chapter V. However, many actual problems do not deal with priorities, so some other approach would need to be developed, possibly from VAM.

Finally, most assignment problems are also scheduling problems.
This research has concentrated on assignment methods. The scheduling logic for the artillery problem was not the result of a thorough investigation. Therefore, further research is necessary to develop methods for dealing with problems where assignment and scheduling must be done together, with emphasis on scheduling techniques.

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APPENDIX A

PROGRAMS FOR TESTING BASIC METHODS

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FORTRAN IV G LEVEL 21


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CeE＊＊WITH RANDOM DIMENSIONS，COEFEICIENTS，NO．RESQUSCES，GHD INFEASIBILITIES． CEFEA IF CESIREC，AN I FUT DATA SET FOE LP SNLYRY HPS CEN SE GENERATED
TAFFSER CV（1500），AV（6n00），AV（2000），P5（2500），S（i506）
CCMMOR：／XECOM／10FT（750）
NTEGER PF
COMOA PEETC／IRDINT
COMMOA PRNTCC／IPRIN
COMON／RNAMC／NAIOES
COWHON／TESTC／MTEST
CCMいOK／LFC：M／LFFLA
COQSOO FFAD APPROX NO VRLS WANTEC，RANOOM SEES，DOINT SUITCH，GND SAUPLE
C＊EEES SIZE（FOR RANDCM－GUIDEN METHONS）OR NO Q＇S WANTER（FCR VAKI）．
C＊＊日＊MTEST，TELLS IF NEXT CARN（S）ARE FOR LPVAX OR FRF PRESRECIFIED RHSTS

```

```

C＊＊＊＊－$\quad$＝LPMLX LISED N TIMES ON SETS OF DATA CADDS CONSISTIRG
COA＊E＊THAT PAETICULAR RHS．

```

``` COAOO EXTRA RATA CAPD WILL PE IISFN AS PHS IN GENERATING
CDOOO D DATA DECK FRZ MFS TO USE TO GET LP SGLA．
Coooes LPFLAG TELLS IF DATA DECK FOR LF SOLN RY MPS IS XANTED．
C＊＊日＊LEFLAG： \(0=\) NO MPS DECK： \(1=\) DECK 8 ALL ELSE； 2 EDECK \(\&\) HOTHINO ELSE
C\＆OEOH IGPEED CONTROLS IMPROVEMENT HEURISTIC：\(=\) NONE， \(1=\) GREEOY． 2 E CRAFTY
```



``` IF（NOVBLS．GT．9000）GO TO 98
fORMATIET10
NRITE（E．223）ISEFD
MET！1：5E＝2＝1．111
Cwoer．READ UIMESSIONS \(A N D\) NO．RESOUPCES，THEN PRINT THEK RERD（E．1） \(\mathrm{KN}, \mathrm{NN}, \mathrm{PP}\)
पRITE1S，ट233）MM，NN．PO
2233 FCOMATI：OMM，AA，PP \(=1.3(15,0\) ．\()\)
C＊＊＊＊CALL SUSRDUTINE TO GENERATE COEFFIS I INFEASIBILITIES．
CALL MATGEN（CV，AV，MM，NN，PP）
Cone．．PRINT FROALEM DATA IF NESIRED． IF（IPGILTLEE．O）GO TO 33
Ceeore CALL SUPFoutine to usf gne soln method witi several rhits
33 CALL SCLOCD（CV，AV，BV，NM，NK，PP．PS．5）
CO＊E日 GENEFATE CATA SET FOR LP SOLN（RHS MUST GE READ FROM A CARDS PEAC（5，1）IRHS
```



```
DO \(3323 I=I\) ISTOP
RV（I）\(=1 R H S\)
\(3333 \mathrm{RV}(I)=\) IRHS
CPLL MPSEENTCV，AV，RV，MN，NN，PP
98 WRITE（ 6,991
99 FORMAT（＇i．，50X．0＊＊NORMAL END OF JOB＊＊OD
STOP
END
```


## OOPTIONS IN EFFECT ID，EBCDIC，SOURCE，NOLIST，NODECK，LOAD，NOMAP －OPTIONS IN EFFECTO NAME $=$ MAIN ，LINECNT＝ 60


-CPTIDRS IN EFFECT: ID,EBCDIC,SOURCE,NOLIST, NODECK,LDAD,NOMAD
GPTIONS IN EFFECT NAME = MATGEN , LINECNT = 60
STATISTICS: SOURCE STATENENTS = 23. PROGRAM SIZE 1224
statistics. No oiagnostics generateo

-OPTIONS IN EFFECT: IO,EBCDIC,SOURCE,NOLIST,NODECK,LOAD,NOMAP

*STATISTICS NO DIAGNGSTICS GENERATED

```
SUBROUTINE SOLOOPIC, A,R, PM,NN,PD,PS,S
C***E CALCULATES UNCONSTRAINED ODTIMU\# TMEN QETAINS SOLUTIONS FOR SEVERAL OIFFERENT PHSIS GY REPEATEO CALLS TO \(A\) SOLLTION SUZROUTINE THAT **. USES ONE OF́ THE HEURISTICS.
COMMCN SEEEC/ ISEED
COMMCN /SEEDC/ ISEED
COMMSN /TESTC/ MTEST
COMMOV /LPCOM/ LPFLAG
TNTEGER PP,C,A,B,P
INTEGER PS.S
OIMENSICN PS(MM,NN), S(MM,NN)
OIMENSION C(MM,NN),A(MM,NN,PP), B(MM,PP)
\(\mathrm{N}=\mathrm{N} N\)
\(\mathrm{M}=\mathrm{MN}\)
\(=2 p\)
WRITE (ó,5)
**** FOMMAT ('1;,30X,1*** INFO ABSUT UNCONSTRAINED OFTIMUM ***') CLEAR gis FOR ACCUMHLATING RESOURCES PEOO BY UNCONSTR OPT
DO \(10 \mathrm{~K}=1 . \mathrm{F}\)
: \(0 \quad 8(I \cdot K)=0\)
C*** FIND UNCONSTR OPT AND ACCUM ITS EESCE REOTS: FIND RHS NEEDED TO MAKE - UnCOAStr opt feas: finc max feas ci(oj)
Pestcp=0
wicsum \(=?\)
\(\cdots \times \cos T=0\)
\(0020 \mathrm{~J}=1, \mathrm{~N}\)
\(\mu I N C=C(1, j)\)
IMC=1
DO \(15 \mathrm{I}=2 . \mathrm{M}\)
ICIJ=C(I.J)
IF(IMXCOST.GT.ICIJ).OR.IICIJ.GT.90001) 60 TO 14
NXCOST=1CIJ
14 TF MINCCLE.ICIJEO TO 15
KINC=ICI
15 CONTINUE
IF MINC.LT.9nON)GO TO 17
C**** FIXUP FGR TASK WHERE ALL AGENTS ARE FLAGGED INFEAS IMC=NOFANOU(ISEED) +1
MINC=100n*aAKDU(ISEED) \&
C(IMC,J) = IINC
OO \(1 \in K=1, P\)
16 A(IMC.J,K) \(=1000\) जRAF:OU(ISEED) +1
WRITE( 6,165 ) J.IMC.MINC, (A(IMC.J,K), K=1,P)
165 FORMAT('OTASK',IA,' INFEAS FOR ALL AGENTS -- NEW C AND A VALUES'.
```



```
TOPT \((J)=I M C\)
1OPT (J) \(=1 M C\)
DO \(19 \mathrm{~K}=1, \mathrm{P}\)
E(IMC,K)=B(IMC,K)+A(IMC,J,K)
IF (B(IMC,K).GT.IRSTOP) IRSTOP=B(IMC,K)
19 CONTINUE
20 CONTINUE
```



```
22 FORMAT (YOUNCONSTR OPT COST \(=1,17 . / \%\) -OASGMT VECTOR:, 2215,/,(15x.2215))
```

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```


0101
0102
0102
0103
0104
0105
0105
0106
0107 MNCSUM=NNCSUM+MINE
5 continue

46 FGEMATI'OUNCONSTR OPT COST FOR TIIS RHS IS :.IT.': ASGT VECTOR: \(\cdot\) *(13014)
48 CALL SOLLER (C, A, B,IB,MK,NN,PP, HXCOST, PS, S \()\)
GO TO 50
END
END
-OPTIONS IN EFFECTA ID,EBCDIC,SQURCE,NOLIST,NODECK, LOAD,NOMAP
-OPTIONS IN EFFEST. NAME = SOLGCP - LINECNT = 60
-OPTIONS IN EFFEST* NAME = SOLGCP - LINECNT = \(\quad 60\)
STATISTICS* NO DIAGNOSTICS GENERATED
statistics* no diagnostics generated


```

-OPTIONS IN EFFECT* ID,EBCDIC,SOURCE,NOLIST, NODECK,LOAD.NOMAP
-OPTIDNS IN EFFECT NAME = MPSGEN - LINECNT = 60 STATISTICS* SOURCE STATEMENTS = 83,PROGRAM SIZE = 2284 STATISTICS NO OI\&GNOSTICS GENERATEO

```
```

FORTRAN IV G LEVEL 21 SOLVER OATE $=78295$ 16/12/22 PAGE OOOI
SUBROUTINE SOLVERIC,A,R,IR,MA,NN,PP,MXCOST,PS,S

```

```

    INTEGED Z,C',H(750),W(750),X3(750)
    COMMON IXECOMIIOPT(750)
    EQUIVALENCE (XQ(1),ICPT(I))
    EQMENSION IP(TSO)
    OINENSION IXESAV(750
    COMman sracec/ tG=EED
    CGMMON/SWACC/ IGREED
    COMMOA /PRNTC, IPRINT
    jNTEGER C,A,R.P.PP
    INTEGER PS,S
    DIMENSION S(MM,NN),PS(MM.NN)
    DIMENSION C (MM,NN),A(YM,NN,PP),B(MN,PP)
    iNTEGER CBIG
    N=MM
    P=P?
    C**O\& COST OF LNASGD TLSK IS NO PASKS TIMES MAX FEAS COST
***.. THIS GUAFAqTEES that a SCLN COVEPING N\&I tASKS IS ChEAPE: than
A SCLN COVERING N OR FEWER TASKS.
INFCST=MXCOSTON
WRITE (6,3)
3 FORMAT(OO*E\# VAMI ***)
C**** MAKE NAPIGOS ODD IF IT IS EVEN
C***O CALCULATE INCRENE:TTS FGR E < .25 AND O >= . 25
OOLT25=1.1(2*(NRIGOS-1)
DQGE25=3.*EQLTZ5
CALCULATE ITERATION NO. WHERE BIGGER INCREMENT STARTS BEING USED
ISTEPN=NAIGOS/2
C**** CALCULATE ANO SUM INEFFICIENCIES(S); SUM COSTS (C). (FEAS CELLS ONLY)
SUMS=0.
00 1 I=1,N
DO 1 J=1,N
ICIJ=CII.j
IF(ICIJ.GT.9000)GO TO 1
SMAX=FLOAT(A(I,J,1))/
IFO 2 K=2,P
STEMP=FLOAT(A(I,J.K))/IB
IF(STEMP.GT.SMAX)SMAX=STEMP
\& CONTINUE
SUMC=SUMC+ICIJ
SMAX=SMAXG1000.
IF(SMAX.GT.1000.)SMAX=1000
SUMS=SUMS+SMAX
1 contIMUE
FESLMC/SURS
O=0.
C**** BIG DO-LOOP GENERATES THE NO. OF SOLNS SPECD

```

C*E*** IF MAX PENALTY & O NO MORE ASGTS ARE FEAS. CALCULATE FINAL INCREMENTS
C*E.& IN COST & NO. UNASGO TASKS, THEN FLAG CORRES ELEMENTS OF ASGT VECTOR.
        IFIMAXPENAGE.OIGO TO I8
        IUAOO=N-j+1
        CE:U=INFCSTOTUADO
        C=i\mp@code{luado}
        IF(x9(JJJ). ¿Q.0) xB(JJJ)==-1
    177 CONIINUE
    C**** SET FLAG FOR NO MCRE ASGTS FEAS
        NOMO=1
        IBIG=-1
        G0 10 80
    CeO**O YAKE SOME CTHER PENALTY MAX NEXT TIME
    CO**OH(USTG)=-1
        00 2? I=1.M
        *2(I)=CI!,JeIG
        0075 I=1,M
    23 MMIN=WII
        CO 25 II=1.M
        IF(:III).GE,WMIN) GO TO 25
        MMN=:III
    5 conimNuE
        IF(*MiN.GT.9000)GO TO 45
    C**** CHECK IF RESOURCES OK
        00 30 K=1,P
        IF(A(IRIG,JBIG,K).GT.B(IRIG,K))GO TO 40
    30 CONTINUE
    ***** RESGURCES OK -- ASSIGN
            00 35 K=1,P
        K(FB(IBIG,K)-A(IRIG.J3IG,K
    35 CONTIPIUE
        CEIG=C(IAIG,JAIG)
        CEIG=CIIN
        * resources not ox -- tay next cheapest agent
    40 W(IFIG)=9999
        60 to 23
    CG*OO* NO FEAS AGENT FOR THIS TASK -- COST IS AIG 2 FLAG IS -1
        45 CRIG=INFCST
        IGIG=-1
        u=u+1
        GO ro 80
    C****S CONTINUE TO COST AND UPDATE ASGMT VECTOR
        80 2=Z+CBIG
        XB(JAIG)=IBIG
        o continue
    C***** SCLUTION COMPLETE
    C***** INITIALIZE FLAG TO CHECK FOR NEW GEST SOLN
    C***** PUEEST=O PRINT OUT ALL. NEW PEST SOLNS
        IF(NSOLN.GT.1)GO TO 120
    105 WRITE(6.110)
    110 FORMAT| NEW BEST SOLN ***UI
```

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| 0001 | C＊＊＊＊ Cどあ＊＊ C＊＊＊＊ C＊＊＊＊ | SUBROUTINE PENCOL $P$ PS．MM，NN，PP，A，R，JJ，IN，II，121 <br> THIS SUBECUTiAE CALCULATES A PENALTY＂IH＂as tide oifference between THF TWO SHALLEST FEASIRLE ELEMENTS（MINZ－HINP）CF THE JIH COLUMA OF P the indexes of wini and minz are returveo in il ave iz so checking for tine necessity of penalty recalculaticn can be gpeeded up． |
| :---: | :---: | :---: |
| 0002 |  | ！VTEGEF PSPFP．F．A．8 |
| 0003 |  | DIMENSION PS（HM），A（MM，NN，PP），$B$（MM，PP） |
| 0004 |  | $\mu=\mu \mathrm{M}$ |
| 0005 |  | $\mathrm{N}=\mathrm{Ni}$ |
| 0006 |  | $p=p \mathrm{P}$ |
| 0007 |  | Jこう」 |
| 0008 |  | MINP＝95949 |
| 0009 |  | $11=0$ |
| 0910 |  | $00101=10 \%$ |
| coll |  | TOS $=5 S(!)$ |
| 0912 |  | IF（IIPS．LT．0）．OR．（IPS．GT．9000））G0 TO 10 |
| 0013 |  | $0 \mathrm{C} 5 \mathrm{~K}=1 . \mathrm{P}$ |
| 0014 |  | IF（A）I，J．K）．LE．E（I，K））GO TO 5 |
| 0015 |  | PS（I）$=-125$ |
| 0016 |  | GO T0 10 |
| 0017 | 5 | continue |
| 8018 |  | IF（：PS．GE．MINP）GO TO 10 |
| 0019 |  | －1NP＝1PS |
| 0020 |  | I1＝1 |
| 0021 | 10 | continue |
| 0022 |  | MIN2＝98998 |
| 0023 |  | $\begin{array}{ll}12 & =0 \\ 00 & \\ 1\end{array}$ |
| 0024 |  | $n 020 I=1, M$ IPS $=$ PS（I） |
| 0025 |  | IPS＝PSII） |
| 0026 |  | IF（（IPS．LT．0）．ER．（İ．EQ．II）．OR．（IPS．GT．9000））60 T0 20 |
| 0027 |  | $0015 \mathrm{~K}=1, \mathrm{P}$ |
| 0.328 |  |  |
| 0029 |  | FS（I）＝－Irs |
| 0030 |  | EO TO 20 |
| 0031 | 15 | COATINLE |
| 0032 |  | IF（IPS．GT．MINZ）GO－TO 20 |
| 0033 |  | MINZ＝IPS |
| 0034 |  | 12＝1 |
| C035 | 20 | CONTINUE |
| 0036 |  | IM＝MIN2－MINP |
| 0037 |  | PETURN |
| 0038 |  | END |

－OOTIONS IN EFFECT ID，EBCDIC，SOURCE，NOLIST，NODECK，LOAD，NOMAP ©CPTIONS IN EFFECT NAME $=$ PENCOL $\cdot$ LINECNT $=$ 60 TSTATISTICS＊SOURCE STATEMENTS＝ 38, PROGRAM SIZE＝ 1378 －statistics＊no diagnostics generated

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CHE日＊NOTE：THE FOLLOLING LOGIC COMRINES STEPS II．D．2．AND 3．OF RANDR
C＊＊＊＊TO SAVE TIME
C
TRY AGENTS IN RANEON ORDER DURING（NOT AFTER）SHUFFLE PROEESS
$M H 1=* N-!$
$0075 I=1, N u$ ．
CoE®＊＊PICK RANOOM AGENT
ISHUF＝$(M-i) \& F A N O U(I S E E D)+1+1$
IBIG＝AB（ISFUF）
$A B(I S H U F)=A B(I)$
ASII）＝IRIG
C＊AHAO CHECK IF FLAGGEO I：SEASISLE
25 If CCIFIG．jATGI．GT，gnorigo to 40
C＊＊＊＊CHECK IF aESCURCES EK
$0030 \quad K=1, P$
（GIG．K）．GT．E（IBIG．KJ）G0 TO 40
CO＊＊＊RESOUACES OK－－ASSIGN
DO $35 \mathrm{k}=1$ ． P
R（IAIGOK）＝8（IAIG，K）－A（IBIG，JGIG．K）
35 CONTINUE
CBIG＝C（TRIE．JAIG）
C＊＊日ロ GO RẼSOLFCES AET OK－
C＊＊＊＊IF UNLEESS NGRDOY IS LEFT TO TRY，．．．
IFIEND．EQ．1） 00 TO 45
C＊＊＊＊FLAE LAST AGENT AS TRIED．THEN 60 tRy him
IEND＝1
IEIG＝AB（M）
GO
GO TO 25
C＊＊＊＊NO FEAS AGENT FCR THIS TASK－－COST IS BIG\＆FLAG IS－1
$45 \begin{aligned} C P I G & =I N F C S T \\ \text { IBIG } & =-1\end{aligned}$
IBIG＝－1
$\mathrm{U}=\mathrm{U}+1$
GO TO 80
75 CONTINUE
COESOH $A D D$ TO COST ANC UPDATE ASGMT VECTOR
$z=Z+C A_{i} G$
XE（JBIG）＝IBIG
CEEOE SOLUTION CONPLETE
C＊＊＊＊INITIALIZE FLAE TO CHECK FOR NEW BEST SOLN NUEEST＝0
C＊ABAO PRINT OUT ALL NEW BEST SOLNS
IF（NSOLN．GT．l）GD TO 120
105 WRITE $(6,110)$
FORMATI：NEW GEST SOLN＋e．！
NUBEST＝1
$M I N Z=Z$
00115 IXES $=10 \mathrm{~N}$
115 IXASAY（IXBS）$=X B(I X B S)$
60 TO 125
120 ．IF（Z．LT．MYNZ）GO TO 105
IFIIPRINT．LT．11GO TO 500
IF（NSOLN．LE．5）GO TO 125
125 IRCOST＝Z－U＊INFCST

```


\footnotetext{
OOPTIONS IN EFFECT* ID,EECDIC,SOURCE,NOLIST,NODECK,LGAD,NOMAP
OPPIINS IN EFFECT NAME \(x\) SOLVER - LINECNT = \(\quad 60\)
estatistics. no diagnostics generateo
12334
}

```

042
0043
0044
0045
0046
0047
0048
00489
0051
0053
0054
0056
0057
DO $75 I=1,4$
WMIN=W(1)
3 WIN=m
$181 \mathrm{G}=1$
$0025 \quad 11=1$,
$0025 I I=1 . M$
IF (NIII).GE.UMIN) GO TO 25

```

```

$\mathrm{HMIN}=\mathrm{MIII}$
BIGEII
25 CONTINE
IF (MNIN.GT.9302)GC TO 45
C**** CHECK IF OESOURCES OK
$0036 K=1 . P$
IF(AIIPIG.JQIG,K).GT.B(IBIG,K))GOTO 40
30 CONTINUE
C**** RESOUQCES OK -- ASSIGN $0035 K=1$, 0
CEIG=CII
CEIG=C(IPIG.JEIG)
GO TO
C**** RESOLRCES NOT OK -- tRY NEXT CHEAPEST AGENT
40 W(IRIG)=9999
C*EAG GO TO 23 NOAS AGENT FOR THIS TASK -- COST IS BIG \& FLAG IS -
45 CEIGIINFCST
$1816=-1$
$U=1$
$G 0 \cdot 1$
GO 10
G0 TO 80
continuf
Ceente $A D D$ TO COST AND UPDATE ASGMT VECTOR $802=2+C E I G$
$X B(J R I G)=I B I G$
10 C CONTINUE
C*EAE SOLUTION COMPLETE
C***** INITIALIZE FLAG TO CHECK FOR NEW BEST SOLN
C**** PFINT OUT ALL NEW REST SOLNS
IFINSOLN.GT.I)GO TO 120
105 WRITE (6.1:0)
110 FORMAT(:*e NEW BEST SOLN *et NUPEST $=1$
MINZ $=2$
DC 115 I $\times R S=1, N$
115 IXBSAV (IXBS) $=\times B(1 \times 8 S$
60 TO 125
120 IF(Z.1T.MINZ)GO TO 105 IFIIPRINT LT IIGO TO 500 IFINSOLN.LE.5:G0 TO 125 GO TOLN.LE.5:GO TO 12
125 IRCOST=2 WRITE (6.127) Z,U,IFCOST.NSOLN
127 FORMAT(' COST:'•I7, ${ }^{\prime \prime}$, NO UNASGD TASKS:'.IS.
', COST OF ASGO TASKS: $1,17.0$. TRIAL NO.: $\cdot 16$ WRITE (6.130) (XB(J),J=1,N)
130 FORMAT: ASSIGNMENT VECTOR: $, 2015,1,(20 X, 2015)$ )
IFIIPRINT.LT.0)GO TO 500
DO $200 \mathrm{~K}=1 . \mathrm{P}$
150 FORMAT: SLACKS

```

-GPTIONS IN EFFECTE ID.EBCOIC,SOURCE,NOLIST,NODECK.LOAD, NOMAP

staristics* no diagnostics generated
```

FORTRAN IV G LEVEL 21 SOLVER $\quad$ DATE $=78295$ PAGE 000I
SUBROLTINE SOLVERIC,A,B.IR,MM,NN,PP,HXCOST,XIJ,S

```


```

c

```
c
C*e*ereren
C*e*ereren
            IATEGER Z.U.T(750),M(750)-XB(750)
            IATEGER Z.U.T(750),M(750)-XB(750)
            n:MERSION IXZSAV(750)
            n:MERSION IXZSAV(750)
            integer XIJ,S
            integer XIJ,S
            DIMEVSION S(WM,NN), XIJ(MN,NN)
            DIMEVSION S(WM,NN), XIJ(MN,NN)
            EGUIVALENCE (XB(1).IOPT(1))
            EGUIVALENCE (XB(1).IOPT(1))
            COMMCN /TESTC/ MTEST
            COMMCN /TESTC/ MTEST
            CGMMON/SNAPC/ IGREED
            CGMMON/SNAPC/ IGREED
            COMVOV/RAVWC/ NAIGGS
            COMVOV/RAVWC/ NAIGGS
            CGMmON /SEEDC, ISEED
            CGMmON /SEEDC, ISEED
            CCMMGN /PFNTC/ IFRINT
            CCMMGN /PFNTC/ IFRINT
            INTEGER C,A,R,P,PP
            INTEGER C,A,R,P,PP
            DIMENSION C(MM,NN),A(MM,NN,PP),B(MH,PP)
            DIMENSION C(MM,NN),A(MM,NN,PP),B(MH,PP)
            integer cbig
            integer cbig
            INTEG
            INTEG
            N=NN
            N=NN
    P=PP
    P=PP
C*E*** COST OF UNASGO TASK IS NO. TASKS TIMES MAX FEAS COST.
C*E*** COST OF UNASGO TASK IS NO. TASKS TIMES MAX FEAS COST.
C***** COST CF LNASGO TASK IS NO. TASKS TIMES MAX FEAS COST, THIS GUAFANTEES THAT A SOLN COVERING N&I TASKS IS CHEAPER THAN
C***** COST CF LNASGO TASK IS NO. TASKS TIMES MAX FEAS COST, THIS GUAFANTEES THAT A SOLN COVERING N&I TASKS IS CHEAPER THAN
C**** A SOLN COVERING N OR FEWER TASKS.
C**** A SOLN COVERING N OR FEWER TASKS.
            INFCST=NXCOSTON
            INFCST=NXCOSTON
            WRITE(6;3)
            WRITE(6;3)
    3 FORMAT(1O*** LPMAX ***:)
    3 FORMAT(1O*** LPMAX ***:)
C**** INITIALIZE VECTOR OF TASK INCEXES
C**** INITIALIZE VECTOR OF TASK INCEXES
            JFRONT=1
            JFRONT=1
            JGACK=N
            JGACK=N
            DO 1 J=1,N
            DO 1 J=1,N
            XB(J)=0
            XB(J)=0
            MO2I=I:M
            MO2I=I:M
            T(JFACK)=J
            T(JFACK)=J
            BACK=JEACK-1
            BACK=JEACK-1
            XB(J)=I
            XB(J)=I
            GOTOI
            GOTOI
            2 CONTMRONT)=J
            2 CONTMRONT)=J
            JFRONT = FFRONT +1
            JFRONT = FFRONT +1
            1 continue
            1 continue
            NM=JFRONT-2
            NM=JFRONT-2
            NM=JFRO
            NM=JFRO
            NN=NM+1
            NN=NM+1
C*a日** DEFAULT SAMPLE SIZE IS 10
C*a日** DEFAULT SAMPLE SIZE IS 10
    IF(NBIGQS.LT.1) NEIGQS=10
    IF(NBIGQS.LT.1) NEIGQS=10
    Co*** bIG DO-LOOP GENERATES THE NO. OF SOLNS SPECD IN SAMPLE SILE
    Co*** bIG DO-LOOP GENERATES THE NO. OF SOLNS SPECD IN SAMPLE SILE
    Ce#*** (REIINITIALIZE NO. UNCOVERED TASKS & OBJ FUN VALUE
    Ce#*** (REIINITIALIZE NO. UNCOVERED TASKS & OBJ FUN VALUE
        l
        l
    C***** (RE)INITIALIZE RHS'S
    C***** (RE)INITIALIZE RHS'S
        O0 5 I=1,M
        O0 5 I=1,M
    5B(I,K)=IB
```

    5B(I,K)=IB
    ```
```

ORTRAN IV 6 LEVEL 21 SCLVER DATE $=78295$ 21/34/38 OAGE 0002
ceete* SHUFFLE INDICES OF TASKS HAVING NO XIJ = 1
DO 29 J=IONMM \& RANOU(ISEFD)*J\&2
JSHAP=T(J)
JSWAPET (J)
T(JSHUF)=JSWAP
O CONTINUE
C*O*** ASSIGN TASKS: FIRST WHERE SOME XIJ = il CIHERS IN RANDOM ORDER
DO 10J J=1.N
~EX=NP1-J
***** GET INDEX FOR NEXT TASK
C**** IF XIJ = !, MAKE CORRES ASGT. OTHERNISE, GO OY DESCENDING XIJ VALUE.
CE*** IF NO FEAS XIU > O. ASSIGN EY ASCENDING COST.
IBFLAG=0
IF(JAX.(E.NJ)GO TO 2021
IRIG=XB(JEIG)
IRFLAG=1
202100 2202 I=1.M
IWI=1000-XIJII,JBIG
F(IWI.LT.0)IWI=999
IFIIWI.EO.1000)IWI=1000+C(I.JBIG
W(I)=T4I
2202 cOntlmus
33 CO 75 I=1.M
IF(IAFLAG.EQ.I)GO T0 3533
23 kMIN=W(l)
IEIG=1
D0 25 II=1,M
IF(W(II).GE.WMIN) GO TO 25
MIN=W(II)
IGIG=II
25 CONTINUE
IF(nMIN.GT. 9000)GO TO 45
Cooes CNECK IF RESOURCES OK
DC 3n }\textrm{K}=1.\textrm{F
IF(A(IHIG,JRIG,K).GT.R(IRIG.K))GO TO 40
30 CONTINGE
***\&* RESOURCES OK -- ASSIGN
3533 DO 35 K=1.f
B(IGIG,K)=B(IEIG,K)-A(IBIG,JBIG,K)
35 CONTINUE
CSIG=C(IBIG.j8IG)
60 TO 80
Co\&: PESOURCES NOT OK -- TRY NEXT CMEAPEST AGENT
0 w(1EIG)=9999
Cont** NO FEAS AGENT FOR THIS TASK -- COST IS BIG \& FLAG IS -I
45 CBIG=INFCST
IBIG=-1
u=u+i
GO TO 80
75 CONTINUE COST AND UPDATE ASGMT VECTOR
80 z=z+CBIG
100 CONTINUE

```

```

FORTRAN IV 6 LEVEL 21 SWAPPR DATE $=78295$ 16/1R/22 DAGE O001

| 0001 | SUQROUTINE SWAPPR (C,A.BAMM,NN.PP.INFCST, 2 ) <br> C**** THIS SURPOUTINE IS "CPAFTY," HGREEOY," OR DCES NOTHING AT ALL. <br>  |
| :---: | :---: |
| 0082 | INTECE $\times$ O,C,A,B,PD,D.Z |
| 0003 |  |
| onct | Conucy /xacons:00t(750) |
| 0035 |  |
| 0906 | Cowwos 15wacti icueso |
| 0007 | comuon /panitc/ Ifaiht |
| 0008 | OIMENSICN IHEAD(2.2) |
| $9 ¢ 09$ |  |
| 0010 | ?F!:EDEEO.LT.I)RETUNN |
| 0011 |  |
| 0012 | 16 FCAMAT(In**E ',2A4,'0**) |
| Col3 | $\cdots=\mu \mathrm{c}$ |
| 0014 | Sand |
| 0015 | EPP |
| 0016 | $M P=N+1$ |
|  | C Leenee RETURN HERE AFTER MAKING SWAP C CeE*es |
| 0017 | $1 \text { ISWAD }=0$ |
| 0018 | iCMANG=0 |
| 0019 | Ceoeet $J=1 \mathrm{l}$ is index of Left-hand trial task. il is current acent for task ul |
| 0020 | 2 IL=x号(J) |
| 0021 | CILUL=INFCST |
| 0022 | IF (IL.GT.O)CTLJL=CIILOJ) |
| 0623 | IF(CILUL.GT.9000)CILJL=iNFCST |
| ceza | Coen*o ILZ ILT IS index of trial new agent for task jl |
| C025 |  |
| 0635 | CILZUL=INFCST |
| 0 C 27 | iF(IL?.LT.MP)CILZJLEC(IL2.JL) |
| 6023 | IFICIL2JL.GT.9000)CIL2JL=INFCST |
| 0029 | C*E*** JP= JR i is index of right-hand trial task ir is index of curpent agent |
| 0030 | $4 \mathrm{IR}=\times \mathrm{P}$ (JP) |
| 0031 | CIPJR=INFCST |
| 0032 | IFIP.GT.OICIRJR=CIIR.JR) |
| 0033 | IFICIRJR.GT.9000)CIRJR=INFCST |
| 0034 | C**e* IRzzi IRE IS INDEX OF TRIAL NEW GENT FOR TASK JR |
| 0035 | 5 IFIIRZ.EG.IRIGO TO 7 |
| 0036 | CIR2JR $=1 N F C S T$ |
| 0037 | IF(IR2.LT.MP)CIRZJR=C(IR2,JR) |
| 0038 |  |
| 0039 | ICELTZ CIILJL CIRJR-CILZJL-CIRZJR |
|  | CeSo*e CHECK IF SHAP IS POTENTIALLY PROFITABLE |
| 0040 | IF (IIELTZ.LE.0)GO TO 7 |
|  | Can*et IF SO. CHECK IF RESOURCES OK WITH FOL DO-LOOP. |
|  | Centet APPARENT CLUMSINESS OF LOEIC IS DUE TO POSSIBILITY OF EQUALITY OF ROW Ceenen INDICES, AND POSSIAILITY FOR ROW INDICES TO. INDICATE THAT TASK UNASGD |

```



OOPTIONS IN EFFECT* 10,EBCDIC,SOURCE,NOLIST,NODECK,LOAD,NOMAP
CPIIONS IN EFFECT NAME = SWAPPF - LINECNT = 60
STATISTICS SOURCE STATEMENTS = 121.PROGRAM SIZE = 4376
-statistics* No diagnostics generated
estatistics* No oIagnostics this step
\begin{tabular}{|c|c|}
\hline 0001 & FUNCTION RANDU(ISEEDX) \\
\hline 0002 & :SEED=15EEDX \\
\hline 0003 & ISEED \(=15 E E D .16807\) \\
\hline 0004 & IF(ISEED)1.i.2 \\
\hline 0005 & 1SEES \(=15 E E D+2147483647 \cdot 1\) \\
\hline 0006 & 2 PANDU=1SEEG*4.656613E-10 \\
\hline 0007 & ISEEDX \(=15 E E D\) \\
\hline 0008 & PETURN \\
\hline 0009 & ENO \\
\hline
\end{tabular}
-JPTIONS IN EFFECT IO.EACDIC,SOURCE,NOLIST, NODECK,LCAO,NOMAP
-GPTIONS IN EFFECTE NAME = RANDU - LINECNT = 60
9,PROGRAM SI2E
```

CONTROL PROGRAM COMPILER - MPS/360 V2-MII


## APPENDIX B

## OUTPUT SAMPLES FROM PROGRAMS IN APPENDIX A

SEED $=1122334455$

```
MHONN,PP = 5; 10, 1,
```

|  |  | MATRIX OF C(I.J) COEFFICIENTS (9999=INFEASIBLE) |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  |  |  |  |  | TASK | NUMBERS: |  |
|  |  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |  |
| AGENT NO. | :: | 804 | 79 | 570 | 447 | 855 | 645 | 525 | 887 | 755 | 847 |  |
| AGENT MO. | 2: | 498 | 774 | 233 | 93 | 290 | 520 | 963 | 671 | 457 | 169 |  |
| AGENT NO. | 3: | 221 | 9999 | 815 | 898 | 268 | 401 | 937 | 515 | 9999 | 46 |  |
| AGENT NO. | 4: | 654. | 954 | 794 | 13 | 555 | 819 | 9999 | 504 | 486 | 789 |  |
| AGENT MO. | 5: | 753 | 607 | 51 | 213 | 9999 | 791 | 114 | 566. | 478 | 9999 |  |
| - |  |  |  |  | - | - . | .- |  |  |  |  |  |




COST: 40934 . NO UNASGD TASKS: $4 . \operatorname{COST}$ OF ASGD TASKS: 2374: TRIAL NO.: 4
ASSIGIJNFNT VECTCR: 4 1 2 -1 -1 5 -1 5





** GREEDY ***
FINAL SWAP RESULT: COSTE $30531 \%$ ASSIGNMENT VECTOR WAS:
** INFO ABOUT UNCONSTRAINED OPTIMUN
-**
UNCONSTA OPT CUST $=2154$
ASGMT VECTOR: $3 \quad 1 \quad 5 \quad 4 \quad 3 \quad 3 \quad 5 \quad 4 \quad 2 \quad 3$
$\begin{array}{cccccc}\text { RESOURCE REOTS OF UNCONSTR OPT: } \\ \text { RESOURCE 1: } & 199 \quad 663 \quad 854 \quad 368 \quad 460\end{array}$

SOLUTION FOR ALL B(I,K) $=630$

** RANDC *e
**. NEW BEST SOLN *.*

-e* GREEDY ***
FINAL SWAP RESULT: $\operatorname{COST}=24828$ ASSIGNMENT VECTOR WAS:


** GREEDY ***
FINAL SWAP PESULT: $\underset{5}{\operatorname{COST}}{ }_{3} 2482:$ ASSIGNMENT VECTOR WAS:
21542
*** GREEDY ***
FINAL SWAP RESULT: COSTE 24828 ASSIGNMENT VECTOR WAS: $21 \begin{array}{lllllllll}2 & 5 & 2 & 3 & 5 & 4 & 4 & 3\end{array}$

LNCONSTR OOT COST = 2154
ASGMT VECTOR: 3 i 5 4 3 3 5 4 2
 RESGURCE 1: $199 \quad 668 \quad 854 \quad 368460$

SOLUTION FOR ALL $8(I . K)=470$
UNCONSTR OPT COST FOR THIS RHS IS 2183 ASGT VECTOR:
-* vami ees
OEO.O NEW BEST SOLN .EC

** gaEEDr ***
FINAL SKAD RESULT: COSTE 205808 ASSIGNMENT VECTOR WASZ
$0=0.05000$
$0=0.10000$
$0=0.15000$
$0=0.20000$
$0=0.25000$
$0=0.40000$
$0=0.55000$
$0=0.70000$
COST: NEW BEST SOLN *** TASK, NO UNASGD TASKS: 1, COST OF ASGD TASKS: 2554, TRIAL NO.: 9

*** GREEDY ***
FINAL SWAP RESULT: COST= $12194:$ ASSIGNMENT VECTOR WAS:
$3120 \quad 1 \quad 1 \quad 5 \quad 5 \quad 4 \quad 3$
$0=0.85000$
$0=1.00000$
** GREEDY ***
FINAL SWAP RESULT: COST= 12194: ASSIBNMENT VECTOR WAS:

## MATRIX OF C(I.J) COEFFICIENTS (9999:INFEASIBLE)

## task numaers:

|  |  | 1 | 2 | 3 | 4 | 5 |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: |
| AGENT NO. | $1:$ | 804 | 79 | 9099 | 447 | 895 |
| LGENT MO. | $2:$ | 645 | 525 | 857 | 9999 | 847 |
| AGENT NO. | $3:$ | 498 | 774 | 238 | 93 | 9999 |

MATRIX OF A(I.J.K) COEFFICIENTS FOR K= 1 11. E., RESCURCE NO. 11

## TASK NUMBERS:

|  |  | 1 | 2 | 3 | 4 | 5 |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: |
| AGENT NO. | $1:$ | 699 | 199 | 0 | 546 | 765 |
| ACENT NO. | $2:$ | 508 | 860 | 451 | 0 | 922 |
| AGENT NO. | $3:$ | 274 | 918 | 276 | 648 | 0 |


| name |  | INP-DATA |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| ROWS |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
| $L$ | R19011 |  |  |  |  |
| $L$ | R19021 |  |  |  |  |
| $L$ | R10031 |  |  |  |  |
| $E$ | R2sod |  |  |  |  |
| E | R2.902 |  |  |  |  |
| E | R2003 |  |  |  |  |
| $E$ | R2got |  |  |  |  |
| E | R2n05 |  |  |  |  |
| columas |  |  |  |  |  |
|  | $\times 100101$ | FOOgOC | 804.60000 | R10011 | 699.00000 |
|  | $\times 100101$ | F200: | 1.00000 |  |  |
|  | $\times 10002$ | F00000 | 79.00000 | R10011 | 199.00000 |
|  | $\times 100102$ | 22002 | 1.09000 |  |  |
|  | $\times 100103$ | ROOOCO | 99999.00000 | R2003 | 1.00000 |
|  | $x: 00104$ | 800900 | 467.00000 | R10011 | 546.00000 |
|  | $\times 100104$ | 22004 | 1. 30000 |  |  |
|  | $\times 100105$ | R00000 | 99999.00000 | R2005 | 1.00000 |
|  | $\times 100201$ | RCOOOO | 645.00000 | P10n21 | 508.00000 |
|  | $\times 100201$ | R2001 | 1.00000 |  |  |
|  | X:00202 | 200000 | 95999.0¢n00 | R2002 | 1.00000 |
|  | $\times 100203$ | 200000 | 8R7.09000 | R10n21 | 451.00000 |
|  | $\times 100203$ | 22003 | 1.00000 |  |  |
|  | $\times 100204$ | R00000 | 99999.00nno | $R 2004$ | 1.00000 |
|  | $\times 109205$ | P003CO | 99999.00000 | R2005 | 1.00000 |
|  | $\times 100301$ | R00000 | 498.00000 | R10031 | 274.00000 |
|  | $\times 100301$ | 22001 | 1.00000 |  |  |
|  | $\times 100302$ | R00000, | 99999.00000 | R2002 | 1.00000 |
|  | $\times 100303$ | POOOOO | 233.00000 | P10031 | 276.00000 |
|  | $\times 100303$ | R2003 | 1.00000 |  |  |
|  | $\times 100304$ | R00900 | 93.00000 | R10031 | 648.00000 |
|  | $\times 100304$ | R2004 | 1.00000 |  |  |
|  | $\times 100305$ | R00000 | 99999.00000 | R2005 | 1.00000 |
| RMS |  |  |  |  |  |
|  | RHS 1 | R10011 | 740.00000 | R10021 | 740.00000 |
|  | RHS 1 | R10031 | 740.00000 | R2001 | 1.00000 |
|  | PHS 1 | R2002 | 1.00000 | R2003 | 1.00000 |
|  | RHS 1 | R2004 | 1.00000 | R2005 | 1.00000 |
| A OUNDS |  |  |  |  |  |
| UP | EVals | $\times 100102$ | 1.00000 |  |  |
| UP | bvals | $\times 100102$ | 1.00000 |  |  |
| UP | avpls | $\times 100103$ | 1.00000 |  |  |
| UP | BVBLS | $\times 100104$ | 1.00000 |  |  |
| UP | EVBLS | $\times 100105$ | 1.00000 |  |  |
| UP | BV9LS | $\times 100201$ | 1.00000 |  |  |
| UP | BVALS | $\times 100202$ | 1.00000 |  |  |
| UP | gVels | $\times 100203$ | 1.00000 |  |  |
| UP | BVals | $\times 100204$ | 1.00000 |  |  |
| UP | RVPLS | $\times 100225$ | 1.00000 |  |  |
| UP | bVals | $\times 100301$ | 1.00000 |  |  |
| UP | bVbls | $\times 100302$ | 1.00000 |  |  |
| UP | BVBLS | $\times 100303$ | 1.00000 |  |  |

VARIFORM, OBJ $=$ ROO000 , RHS $=$ RHSI


## SECTION 1 －ROWS

| NUMEER | ．．．ROW． | AT | ．．．ACTIVITY．．． | SLACK activity | ．．LOwer limit． | ．．UPPPER LIMIT． | ．Qual activity |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | R00000 | ES | 101：54．51：52 | 101154．51852－ | MONE | none | 1.00000 |
| c | R10cll | ES | 354．03704 | 385.95296 | NONE | 740．00000 | ． |
| 3 | 510021 | es | 508．0こッこ0 | 232.00000 | NSNE | 740.00900. |  |
| 4 | P1C031 | UL | 745.00090 | － | NONE | 740.09090 | ． 54630 |
| 5 | 22001 | EO | 1．00000 | － | 1.00000 | 1.00900 | 647．63519－ |
| 6 | R2002 | EO | 1.00 .500 | － | 1.00000 | 1.00000 | 99999．00900－ |
| 7 | 22003 | EO | 1.00000 | － | 1.00000 | 1.00000 | 837．00000－ |
| 8 | R2004 | E0 | 1.00000 | － | 1.00000 | 1.00000 | 447．00000－ |
| 9 | R2005 | EO | 1.00000 | $\bullet$ | 1.00000 | 1.00000 | 99999．00000－ |

LP SOLN OF MULTI－RESCURCE GENERALIIED ASGT PROBS
78／10：23
SECTIOH 2．－COLUMNS

|  |  | ．COLUMN． | AT | ．．．ACTIVITY．．． | ．．indut cost．． | －．lower limit． | ．．upper limit． | －REDUCED COST． |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 10 | $\times 100101$ | LL |  | 804.00000 | － | $1.00 n 00$ | 156．31481 |
|  | 11 | $\times 100102$ | UL | 1.00000 | 79．0000n | － | 1.00000 | 99975．00000－ |
|  | 12 | $\times 100103$ | LL | － | 99999．0n000 | － | 1.00000 | 99112.00000 |
|  | 13 | $\times 100104$ | 8S | ． 2 2395 | 447.00000 | － | 1.00000 | ． |
| A | 14 | $\times 100105$ | LL | － | 99909．0nnno | － | 1.00000 | － |
|  | 15 | $\times 100201$ | UL | 1.00000 | 645.09000 | － | 1.00290 | 2．68519－ |
| A | 16 | $\times 100202$ | LL | － | 99999．00000 | － | 1.00000 | － |
|  | 17 | $\times 100203$ | 65 | － | R87．0n000 |  | 1.00000 | － |
|  | 18 | $\times 100204$ | LL | － | 99599．00000 | － | 1.00000 | 99552.00000 |
| A | 19 | $\times 100205$ | LL | － | 99599．00000 | － | 1.00000 | ． |
|  | 29 | $\times 100301$ | 85 | － | 498．00000 | － | 1.00000 | － |
|  | 21 | $\times 100302$ | BS | － 0000 | 99999.00000 | － | 1.00000 |  |
|  | 22 | $\times 100303$ | UL | 1.00000 | 238.00000 | － | 1.00000 | 498．22222－ |
|  | 23 | $\times 100304$ | BS | .71605 | 93.00000 | － | 1.00000 | － |
|  | 24 | $\times 100305$ | BS | 1.00000 | 99999．00000 | － | 1.00000 | － |

APPENDIX C

PROGRAMS FOR LIMITED COMPUTER RESOURCES

|  |  |  |
| :---: | :---: | :---: |
|  |  |  |
| 2010 FOR J2＝1 TO 5 |  |  |
| 2020 IF $\mathrm{J} 2=1$ THEN 2060 |  |  |
| 2030 REM TAXE STEPS IN Q |  |  |
| $2040 \mathrm{Q}=0+\mathrm{Q}$ |  |  |
| 2050 R | REM（RE）SET RESOURCE SUPPLIES |  |
| 200́c fop：＝2 io m7 |  |  |
| 2070 ن（ $i$ ）$=3(i)$ |  |  |
| 2580 | $V(1)=T(1)$ |  |
| 2090 NEXT I |  |  |
| 2100 REM LCOP CALC＇S PENALTIES |  |  |
| 2110 F | FOR $J=1$ TO $N$ |  |
| 2120 If J2＞I G0 T0 2170 |  |  |
| 2130 R | REM PENALTY FOR $2=0$ IS EASIER |  |
| $21.30 \mathrm{P}(\mathrm{J})=\operatorname{ABS}(\operatorname{INT}(C(2, J)-C(1, U)+20) / 100)$ |  |  |
| 2：50 G0 | GO TO 2460 |  |
| 2i6？REH：USPACK RESOURCE REQTS |  |  |
| 21？El＝R（1，${ }^{\text {2 }}$ ） |  |  |
| $2150 \mathrm{Rl}=\mathrm{i}$ ：T（E1／1000） |  |  |
| 2190 El＝El－R：＝1000 |  |  |
| 2200 | $E 2=R(2, ~ i) ~$ |  |
| 2210 R | R2＝INT（EL／1000） |  |
| 2230 E2＝E2－R＇̇1000 |  |  |
| 2230 REM L LPACK COSTS \＆ROW INDEXES |  |  |
| 2240 Pl＝C（2，ن） |  |  |
|  |  |  |
| 2260 | P：＝？－－ $1 \times 20$ |  |
| 2270 P2＝C（2，${ }^{\text {c }}$ |  |  |
| 2280 | $C 2=1 \mathrm{NT}(\mathrm{P} 2 / 100)$ |  |
| 2290 P2＝22－C2＝200 |  |  |
| 2330 REM CALC ！NEF＇CY FOR ©ACH |  |  |
| 2310 REM RES＂CE CN EACH MACH |  |  |
| 2320 | Ri＝R1／B（P1） |  |
| 2330 E1＝E1／T（P1） |  |  |
| 2340 R2＝22！${ }^{\text {2 }}$（ 2 ） |  |  |
| 2350 EE＝E2／T（P2）MEF＇CY ON EACH MACH |  |  |
| 2360 REM FIND MAX INEF＇CY ON EACH MACH |  |  |
| 2370 fF El2RI THEN 2390 |  |  |
| 2380 | $E 1=R 1$ |  |
| a 390 if elzR2 then 2120 |  |  |
| 2400 E2＝R2 |  |  |
| 2410 | rem galculate penalty |  |
| 2420 Q1ここーQ |  |  |
| $2430-5=(6)+C 2) / 2$ |  |  |
| 2440 ES＝（El＋E2）／2 |  |  |
| 2460 NEXT J |  |  |
| 2470 C5＝02480 REM UNTIL ALL JOBS ARE ASSIGNED |  |  |
|  |  |  |
| 2490 FOR $J=1$ TO $N$ O |  |  |
| 2500 | REM FIND L＝NO．OF JOB W／MAX PEN | $\sim$ |
| 2520 | L＝1 |  |
| 2530 | FOR J6＝2 TO N |  |

```
2540 IF P(J6)SM6 THEN 2570
2550 Mć=P(\6)
2550 L= \6
25:0 NEXT JE
2590 REM KEEP PEN FROM BEING MAX AGAIN
2590 P(L)=-93ミ#GO
C,
    FOR 1= 1 TC M
2530 IF C&`כGjECS THEN 2?40
2640 cl = INT(Cz/100)
2650 c2=Cz-C\:100
2E60 RZ=R(1,1)
2670 RI = INT(R2/\0C0)
2620 IF R\ > U(C2) THEN 2730
SE30 R2 = R2-? X- 1000
C7j0 IF R2 > V(C2) THEN 2730
2710:5=1
2720 GC TO 2780
2730 HEXT 1
<740 M(L)= - - .
2750 C1 = 50ODCO
27:0 GO TO 231C
27こे u(E2)=u(c2)-R1
27% U(C2)=U(C2)-R1
2&CC A(L)=C2
2% 左 (CL)=C2
2320 NEXT J
2830 PRINT
28LC PRINT 'SOLUTION';U2
2850 IF U6 = O THEN 2900
2C=0 C5 = C5-U6:500000
2870 FOR I = i YO U6
2230 PRINT 1x1;
2890 NEXT I
2900 PRINT 'COST = ',C5
2910 FOR I= 1 TO M
2920 Y1= Y(1) (MACH NO. ',Y1;' ASGD TO:'
2730 PRINT 'MACH NO. ';Y1;' ASGD TO
2940 N2= = 
```



```
2570 Nl = 1 N
2900 PRINT', NOB',z(U)
2990 NEXT J
3000 IF N1 # O THEN 3020
3000 IF NI ## O THEN 3020 **: ,
3010 PRINT IXx* NOTHING **xU 
3030 PRINT UNNUSED TIME:';V(Y1)
3040 PRINT
3050 NEXT I 
3070 PRINT 'UNASSIGNED JOBS:'
3080 U6=0
3090 FOR J = 1 TO N
```

```
1990 REM xxx RANDC xxx
2C10 INPUY Rg
2020 GI= NT* 550000
2030 PRINT 'NO. TRIALS = ?
2040 INPUT 2
C50 KI = 1
050 REM KI & 2 ARE RESET IF
OOTO REM MORE TRIALS ARE WANTED
ORO FOR K = KI TO Z
FLAG FOR INCOMPL. SOLN
2100 U6 = O
2110. REM (RE) SET RESOURCE SUPFLIES
2120 FOR I = 1 TO M7
2430 V(1)}=\mp@code{Q(1)
250 NEXT I
Cl60 REM SHUFFIE INDEXES TO NOES
2170 FOR }\downarrow=N=N\mathrm{ TO 1 STEP -1
2180 51 = 441
2190 RG=RND(R9)
200 C2=INT(Rg'v)+1
210 C4=P(S1)
2230 P(S1)=P(C2)}=C
2240 NEXTJJ
2250 C5 = 0
2250 REM OPTIMIZE JOBS PER SHUFFLED INDEXES
2270 FOR J=1 TO N
2280 L = P(U)
2290 FOR I = 1 TO M
2300 10 =1
23:0 C2=C(1,L)
2320 IF (2>999000 THEN 2450
2330 REM GET COST & ROW INDEX
2540 CI = INT(C2/100)
2350 C2=C2-CI: 100
237C R2=R(1,L)
2380 RI = INT(R2/1000)
2390 IF RI > V(C2) THEN }243
2:00R2 = R2-RIN1000
Z4CO IF R2 S U(C2) THEN 2500
2430 NEXTII
HC REM UNASSIGNED JOB
6450 A(L)=-1
2470 C1 = 500000
2480 GO TO 2540
2490 REM DECREMENT RESOURCES & ASSIGN
2500 V(C2) = V(C2)-R1
2510U(C2)=U(C2)-R2
2520 A(L)=C2
```


## 3030 PRINT 3040 PRINT <br> 3040 PRINT 'NEW RUN'

3050 INPUT YS
30ES REM CHECK FOR RERUN OF WHOLE PROB
3070 REM OR NEW RESOLRCE SUPPLIES
3030 IF YS = 'YES' THEN 3:3C
309C IF YS $\Rightarrow$ 'RHS THEN 3130
3100 GO TO 3149
3:10 RESTORE
3120 GO TO 3149
3130 PRINT
3140 STOP
3150 END
150 END

2650 C. $5=$ C5-U6X 500000
266 C IF US $=0$ THEN 2700
266 IF U6 $=0$ THEN 2
2670 FOR $1=1$ TO U6

26ミ0 NEXT ${ }^{1}$
2700 PRINT ' COST $={ }^{\prime}$, C5
2710 FOR $I=1$ TO M
2710 FOR $I=1$ TO M
2720 Yl=Y(I)
2730 PRINT 'MACH NO. ',YY'' ASGD TO :"
$2740 \mathrm{NI}=0$
2750 FOR $J=1$ TO N
2760 IF $A(J)$ YI THEN 2790
$2770 \mathrm{~N}^{\circ}=1$
2780 PRINT 1 JOB';Z(ひ)
2790 NEXT J
2800 IF NI $\neq 0$ THEN 2820
2810 FRINT $1 \times x \times$ NOTHING $2 \times x$
2820 PRINT 'UNUSED MATL:' ', V(YI)
2830 PRINT 'UNUSED TIME: 'JU(Y 1 )
2840 PRINT
2350 NEXT I
2260 IF UE=0 THEN 2930
2870 PRINT IUNASSIGNO
2270 PRINT 'UNASSIGNED JOBS:'
2990 FOR $J=1$ TO N
2900 IF $A(N)>0$ THEN 2920
2910 PRINT JOB I;Z(U)
2920 NEXT J
2930 NEXT K
2940 REM CHECK FOR MORE TRIALS
2950 PRINT 'MORE TRIALS?'
2950 INPUT Y\$
S70 IF YS 'YES' THEN 3030
2980 PRINT 'HOW MANYT'
$290 \mathrm{KI}^{\prime}=$
3990 Kl $=2+$


```
2000 REM **X METHODS ARE IDENTICAL THRU STATEMENT 1980 *x*
1010 DIM C(7,10),R(7,10), 8(7),T(7),V(7)
1020 DIM A(10),P(10),Y(7),Z(10),U(7)
10j0 REM :%% PREOEFINED DATA :%:
1040 REM SORTED INDEXED COSTS LND
1050 REM PACKED RESCURCE REQUIREMENTS
070 REM LJE I
1070 DATA 4001,6307,7306,8305, 8903,9002,9704
1080 DATA 61019,13015,48036,62033,69039,18057,58025
1090 REM JO R 2
1110 DATA 4804,5605,6303,6805,8701,9=07,099902
?!20 REM NOE 3
1130 OATA 2405,4802,5803,6001,5705,7107,9604
1140 CATA 72045,59063,49051,87000, 次25,27059,82034
1150 REM voe 4
1160 DATA 12:32,3306,3305,5701,7403,8304,8907
1170 DATA 870.'2,12067,43015,34034,65011,92048,54019
100 REM UOB 5
l190 DATA1003,2506,4304,5307,6505,7001,9802
1210 REM JOB G % % % 6405,6703, 2004, 2907,999902
1230 DATA 74024,0,33C25, 6000́2,EEC89,4201d,2.2014
1240 REM UOB 7
1250 EATA 3702,3904,4405,4503,6806,6907,950%
1260 DATA 53012,89024,45023,92076,31044,84059,32019
1270 REM JOE 8
1230 DATA 1102,2903,4107,7101,7705,7906,9704
1290 DATA 74071,84069,52085,96C46,74095,50C25,55016
1300 REM JOB9
1310 DATA 2001,3505,4404,4602,48C5,5803,5107
1330 PEM NCS IO
1240 DATA 1002,1106,1601,2105,7107,7304,999903
13:0 DATA 53056,71075,0,62056,90047,32048,86075
1360 REM ARRAY DIMENSIONS
1370 M7 = ? 
1380.N7 = 10
1390 REN READ PREDEFINED DATA
140C FOR J=1 TO N7
1420 READ C(1,N)
1420 NEXT I
1440 FOR i = 1 TO M7
1450 READ R(I,U)
1460 NEXT I
1 4 7 0 \text { NEXT}
1480 REM I NPUT ADDITIONAL DATA
1490 PRINT 'NO. MACHINES ?'
```

1000 REM $\times$ ：X METHODS ARE IDENTICAL THRU STATEMENT $1980 \times x \times$
1020 DIM（ 7,10$), R(7,10)$, （ 7 ），T（7），V（？）
1030 PEM ：$\because \% ~ P S E E E F I N E D$ DATA $\because: \%$
1050 REM PACKED RESCURCE REQUIREMENTS
1070 REM LJE 1
1080 DATA 61019，13015，48036，62035，69039，18057，58025
1090 REM JOR 2
1110 DATA $16016,0,28053,38089,12059,950: 9,50033$
120 REM LOE 3
1140 CATA $72045,59063,49051$ ，87000̂， $3 \div 225,27059,82034$
1160 DATA 12：32，3306，3305，5701，7403，8304， 8907
1170 DATA $87082,12067,43025,34034,66021,92048,54019$
1190 DATALO03，2506，4304，5307，6505，7001，9802
120 DATA $43050,81039,67081,89072,78640,85051,79052$
2220 DATA 2501，3606，6405，6703，2004，8907，999902
1230 DATA 74024，C，33C25，6000́2，EEC89，42012， 2.2014
1240 REM UOB
1260 DATA $53012,89024,45023,92076,31044,94059,32019$
1270 REM NOE $8,2903,4107,7101,7705,7906,9704$
1230 DATA 1102，2．903，4
1290 DATA $74071,84069,52085,96646,74095,50025,55016$
1300 REM JOB 9
DATA $75072,48002,91055,85059,46059,53059,62049$
1240 DATA $1002,1106,1601,2105,7107,7304,999903$
1350 DATA 53056，71075， $0,62056,90047,32048,86075$
$1370 \mathrm{M7}=7$
$1380 . N 7=10$
1390 REM READ PREDEFINED DATA
$\begin{array}{ll}140 C \text { FOR } J=1 & \text { TO N7 } \\ 1410 \text { FOR } & =1 \text { TO M7 }\end{array}$
14 20 READ $C(1,4)$
1430 NEXT ！
1450 READ R $(I, J)$ TO M
1470 NEXT J
1480 REM 1 NPUT ADDITIONAL DATA
1490 PRINT INO．MACHINES
1490 PRINT＇NO．MACHINES ？＇

```
1500 INPUT M
```

1500 INPUT M
1510 M9 = M + I
1510 M9 = M + I
1520 M. =M-1
1520 M. =M-1
1530 PRINT 'NO. JOBS ?
1530 PRINT 'NO. JOBS ?
1540 :NPUT N
1540 :NPUT N
l
l
1570 FOR I = 1 TO M
1570 FOR I = 1 TO M
1580 INPUT YC
1580 INPUT YC
1500 FR!NT 'ENTER';N;'NOS NOS. IN ORDER'
1500 FR!NT 'ENTER';N;'NOS NOS. IN ORDER'
1610 FOR J = 1 TO N
1610 FOR J = 1 TO N
1E20 INPUT Z(U)
1E20 INPUT Z(U)
1630 NEXT J
1630 NEXT J
1540 PRINT 'ENTER: MATL THEN TIME FOR:
1540 PRINT 'ENTER: MATL THEN TIME FOR:
1650 FOR I = 1 TO M
1650 FOR I = 1 TO M
1560 Y1= Y(1)
1560 Y1= Y(1)
1670 PRINT 'MACHINE \&';Y(I)
1670 PRINT 'MACHINE \&';Y(I)
1680 INPUT R(Y2),T(YI)
1680 INPUT R(Y2),T(YI)
1690 NEXT I CHECK IF RERJN WITH
1690 NEXT I CHECK IF RERJN WITH
171C REM NEW RESOURCE SUPPL!ES
171C REM NEW RESOURCE SUPPL!ES
172O IF YS = 'RHS'THEN 2000
172O IF YS = 'RHS'THEN 2000
2730 REM IMITIALIZE NOR INDEXES
2730 REM IMITIALIZE NOR INDEXES
1740 REM FOR SHUFFLING AND
1740 REM FOR SHUFFLING AND
1750 REM COMPRESS COSTS \& RESOURCES
1750 REM COMPRESS COSTS \& RESOURCES
1760 REM INTO UPPER LEFT CORNER
1760 REM INTO UPPER LEFT CORNER
177C REM OF DATA MATRICES
177C REM OF DATA MATRICES
1780 FOR J = 1 TO N
1780 FOR J = 1 TO N
1790 P(J) = J
1790 P(J) = J
1800に2(U)
1800に2(U)
1810 !2=1 = 1 TO M
1810 !2=1 = 1 TO M
1830 C2 = C(1,L)
1830 C2 = C(1,L)
1840 K=c2-100x(INT(C2/100))
1840 K=c2-100x(INT(C2/100))
1850 FOR 11= I TO M
1850 FOR 11= I TO M
1860 k1= Y(İ) 1 TO M
1860 k1= Y(İ) 1 TO M
1870 IF X K KI THEN 1920
1870 IF X K KI THEN 1920
1880 U(I 2)=R(K,L)
1880 U(I 2)=R(K,L)
1890 v(1 2)=c2
1890 v(1 2)=c2
1900 I 2=12+1
1900 I 2=12+1
1910 :F !2 > M THEN }194
1910 :F !2 > M THEN }194
1920 NEXT II
1920 NEXT II
1930 NEXT I
1930 NEXT I
1940 FOR I=1 TOM
1940 FOR I=1 TOM
1950 R(I, J)=U(I)
1950 R(I, J)=U(I)
1960 C(I,N)=V(I)
1960 C(I,N)=V(I)
1970 NEXT I

```
1970 NEXT I
```

APPENDIX D

OUTPUT SAMPLES FROM PROGRAMS IN APPENDIX C

| No. MACHINES ? | - | $\begin{gathered} \text { SOLUTION } \\ \times \operatorname{COST}=120 \end{gathered}$ |  |
| :---: | :---: | :---: | :---: |
| No. No es ? |  | MACH NO. 1 | ASGD 10 : |
| 3.4 | - | JO 81 |  |
| ENTER 2 MACHINE NOS. IN ORDER |  | JOB 3 |  |
| ? 1 H |  | UNUSED MATL: |  |
| ? 3 | - | UNUSED TIME: 85 |  |
| ENTER 4 JOB NOS. IN ORDER |  |  |  |
| ? 1 |  | MACH NO. 3 | ASGD TO : |
| 2 | - | ve 5 |  |
| ? 3 |  | UNLSEO MATL: 83 |  |
| 15 |  | UNUSED TIME: 49 |  |
| ENTER: MAT: THEN TIME FOR |  |  |  |
| Machine 1 |  | UNASSIGNED JOBS: |  |
| ? 140, 150 |  | JOB 2 |  |
| machine 3 |  |  |  |
| ? 150,130 |  | SOLUTION 4 |  |
|  |  | - COST $=137$ |  |
| SCLUTION 1 | . | MACH NO. 1 | ASGD TO : |
| *COST $=137$ |  | JO8 1 |  |
| MACH NO. 1 ASGD TO |  | JOE 2 |  |
| Joe 1 | - | UNUSED MATL: 63 |  |
|  |  | UNUSED TIME: 215 |  |
| URUSED MATL: 63 |  |  |  |
| UNUSED TIME: 115 | - | $\begin{gathered} \text { MACH NO. } \\ \text { NO } \\ 3 \end{gathered}$ | ASGD TO : |
| MACH NO. 3 ASGD TO : |  | UNUSED MATL: 83 |  |
| UOB 5 - |  | UNUSED TIME: 49 |  |
| UNUSED MLTL: 83 |  |  |  |
| UNUSED TIME: 49 |  | UNA SSIGNED NO ES: JOB 3 |  |
| UNASSIGNED JOES: | $\cdots$ |  |  |
| JOB 3 |  | SOLUTION 5 |  |
| SOLUTION 2 | i: | MACH NO. 1 | ASGD TO : |
| $\times$ COST $=137$ |  | LOB 1 |  |
| MACH NO. I ASGD TO : |  | JOB 5 |  |
| UO8 1 , ASGO 10 |  | UNUSED MATL: 36 |  |
| JOB 2 |  | UNUSED TIME: 8I |  |
| UNUSED MATL: 63 |  |  |  |
| UNUSED TIME: 115 |  | $\begin{gathered} \text { MACH NO. } \\ \text { NO } \end{gathered}$ | ASGD TO : |
| MACH NO. 3 ASGD TO: |  | JOB 3 |  |
| Jo8 5 A | - | UNUSED MATL: 73 |  |
| UNUSED MATL: 83 |  | UNUSED TIME: 17 |  |
| UNUSED TIME: 49 |  |  |  |
|  |  | NEW RUN |  |
| UNASSIGNED JO BS: |  | ? 18 |  |
| JOB 3 | $\cdots$ | xxx END $x$ ( |  |
|  |  | time 0.3 secs. |  |
|  | $\because$ |  |  |


| NO. MACHINES? | - | $\begin{aligned} & \text { TRIAL NO. } \\ & \text { COST }=240^{3} \\ & \text { MACH NO. } 1 \end{aligned}$ | ASED TO : |
| :---: | :---: | :---: | :---: |
| NO. voss ? |  | 10 s ? |  |
| 75 | - | Ј e |  |
| ENTER 2 Machine nos. In ORDER |  | UNLSED MATL: 36 |  |
| P1 |  | UNUSED TIME: 81 |  |
| ? 3 | - |  |  |
| ENTER 4 JOB NOS. IN ORDER |  | MACH NO. 3 | ASGD TO |
| ? 1 |  | UOB |  |
| ? 2 | - | JOB 3 |  |
| ? 3 |  | UNUSED MATL: 73 |  |
| ? 5 |  | UNUSED TIME: 17 |  |
| Enter: matl then time for | - |  |  |
| : $A C H$ ! CE E 1 |  |  |  |
| ? 240,250 |  | TRIAL NO. ${ }^{4}$ |  |
| MACHINE 3 |  | COST $=246$ |  |
| ? 150, 130 |  | MACH NO. 1 | ASGD TO |
| RANDOM SiO. $=$ ? |  | JOB 2 |  |
| ? 5217347 | - | JOB 3 |  |
| No. TRIALS = ? |  | UNUSED MATL: 52 |  |
| ? 10 |  | UNUSED TIME: 88 |  |
| ** NEW EEST SOLUTION |  | MACH NO. 3 | ASED TO |
| TRIAL NO. 1 |  | Jos 1 |  |
| $\times$ COST $=137$ |  | JOB 5 |  |
| MACH NO. 1 ASGD TO : |  | LXUSED MATL: 35 |  |
| Ј 8 |  | UNUSED TIME: 13 |  |
| 1032 |  |  |  |
| UNUSED MATL: 63 |  |  |  |
| UNUSED TIME: 115 |  | TRIAL NO. 5 |  |
|  |  | COST $=240$ |  |
| $\underset{\text { NOB }}{\mathrm{MACH}} \mathrm{NO}^{3} \text { ASGD TO: }$ |  | $\text { MACH No. } \operatorname{SOB}_{1}$ | ASGO TO |
| UNUSED MATL: 83 |  | JOE 5 |  |
| UNUSED T!ME: 49 |  | UNUSED MATL: 36 |  |
|  |  | UNUSED TIME: 81 |  |
| UNA SSIGNED JOBS: JOB 3 | $\cdots$ | MACH NO. 3 | ASGD TO |
|  |  | J08 2 | ASGD 10 |
| xx NEW PEST SOLUTION |  | Јов 3 |  |
| TRIAL NO. 2 |  | UNUSED MATL: 73 |  |
| $\operatorname{COST}=240$ |  | UNUSED TIME: 27 |  |
| MACH NO. 1 ASGD TO : |  |  |  |
| Ј08 1 | , | more trialst |  |
| UOB 5 |  | 3 No |  |
| UNUSED MATL: 36 | - |  |  |
| UNUSED TIME: 81 | - | NEW RUN |  |
|  |  | ? NO |  |
| MACH NO. 3 ASGD TO : | $\sim$ | *ヵ* END *xx |  |
| NE 2 |  |  |  |
| JOB 3 |  | TIME 0.3 SECS. |  |
| UNUSED MATL: 73 |  |  |  |
| UNUSED TIME: 17 |  |  |  |

```
TRIAL NO. \({ }_{24}{ }^{3}\)
    ACH NO. 1
    10 E
NUSED MATL: 36
UUSED TIME: 81
ACH NO. 3 ASGD TO:
JOB 3
NUSED TIME: 73
RIAL NO.
ACH NO. \({ }^{24}\)
JOB \({ }^{2}\)
UNUSED MATL: 52
UNUSED TIME: 88
MACH NO. 3 ASED TO:
    \(\begin{array}{cc}\mathrm{JOE} \\ \mathrm{JOB} & 1 \\ 5\end{array}\)
NUUED MATL: 35
TRIAL NO. 5
AST \(=10240\) ASGD TO:
```



```
USED MATL: 36
ACH NO. 3 ASGD TO :
    JOB 3
UNUSED TIME: 27
MORE TRIALS?
NEW RUN
*꾸 END *xx
TME 0.3 SECS.
```

UNUSED MATL: 73
UNUSED TIME: 17

APPENDIX E

PROGRAM FOR ARTILLERY PROBLEM







```
FORTRAN IV G LEVEL 21 MAIN DATE \(=78295\) 13/38/39 PLGE OOOT
```

SUMEI=0. SUMAMO $=0$
DO $76 \mathrm{j}=1$ INT
c
c
c
$c$
$C$
Lag infeasibilities in ammo, time, and inefficiency matrices
2762 IF (C (I.J).LT.990000.)60 TO 762
$2762 \mathrm{~F}(1, J)=0$.
(I'J) $=1000000$
$S(1 \cdot J)=1000000$.
C Co*** Calculate engagement times
762 EX=A(1.J)/TU(I)-1.
IF((EX-IFIX(EX)).GT.0.nO1)EXEEX+1.
ExIFIX(EX) TIIII)
IF(EX.LT.O.)EX=O
C
$\stackrel{C}{C}$
©ete ADD INFEASIBILITIES FOR NON-MASS TGTS DUE TO TIME OR AMMO

$C(I, J)=1000000$
GO TO 27E2
$c$
$c$
$c$
.
**** Calculate time and ammo inefficiencies
761 RIエE(I,J)/TIME
C**** RZ ADJUST FOR ONE-VOLLEY MINIMUM ON MASS TGT IF NEEDED
IF(IMI(J.li.GT. I).AND.(TUII).GT.R2))R2=TU(I)
R2=E2/A(I)
C**eO* SUILD ITEFFICIENGY MATRIX (APPLYING MAX ALLOWARLE INEFFICIENCY)
$C$
IF(RI-GE.R2) SII, JIERI
IF(R2.GT.R1)S(I,J)=R2
C $\mathbf{C}$.ene. SUM AND COUNT FEASIELE COSTS AND INEFFICIENCIES FOR LATER C*EAE CALCULATIONS OF FACTOR FOR BALANCING COSTS TO INEFFICIENCIES

Sums $=\operatorname{suns}$ •S(I.J)
SSSESSS+1.
SUMAMO=SUM2MO $+R(I, J)$
SUMEI $=$ SUMEI $+E(I, J)$
76 CONTINUE
C
C.*** SET. SWITEH 70 TURN OFF CONSIOERATION OF INEFFICIENCIES FOR UNITS C***** WITH PLENTY OF TIME ANE AMMG TO COVER ALL POSSIELE TARGETS

LGRNG (I) $=0$
IF(SUMEI.GT.(TIMET5) .AND. SUMAMO.GT.A(I)) LGRNG(I)=1
77 CONTINUE
c



```
FORTAAN IV G LEVEL 21 MAIN DATE \(=78295\) 13/38/39 PAGE OOIO
0266
0267
0268
0269
0270


0271
0272
0273
0274
0275
0276
0277
0278
0279
```


## KK=1 <br> $005050 \mathrm{~K}=1$, IEMAX $1 G G(K)=K K$ <br> 5050 KKxKK•IGX(K)

```
5050 CONTINUE
**** APPLY RALANCING FACTOF TO INEFFICIENCIES AND PRINT THE ©*O* EALANCED INEFFICIENCIES
\(008 \quad J=1, N T\)
\(s(1, J)=8 * 5(1, J)\)
8 continue
IFIIPRINT.EQ.0160 TO 1670
PRINT 82.B
82 FOFMAT ( \(4 H 18(x, F 8,3,3 I H)-W E I G H T E D\) MAX(R/A.E/T)-KATRIX:,/,5HOROW:) OO \(69 I=1\), Ni
PRINT 8R,I,(S(I,J),J=1,NT)
```


## 89 CONTINUE

```
C
```



```
C=世**
C
1670 NN=NU 1
DO 9 I \(=1.0\) T:
\(S(N N, I)=500000\).
\(C(N N, I)=500000\)
R(NN,I) \(=1\).
\(E\left(N N_{1} I\right)=T I M E /(N T+100)\)
\(P(N N, I)=500000\).
9 CONTINUE
\(A(N N)=2000000000\).
LGRNG (NN) \(=0\)
SC(N: \()=.001\)
\(T 1(N N)=.001\)
\(T 1(N N)=001\)
\(T U(N N)=1\)
C
C
.
.
.
C**** ****************************************
Ce**** CALL SUBROUTINES FOR SOLUTIONS AND OUTTUT
C
```



```
C*O日* CALL MAIN CONTROL SUBROUTINE MHICH CALLS ALL OTHERS, INCLUC**** DING OUTPUT)
```


## $c$

```
CALL FPBIAS
PRINT 9999
9999 FORMATIIH1.50X.27H** NORMAL END OF JOB ***) STOP
END
```



```
OPTIONS IN EFFECT* NAME \(=\) MAIN • LINECNT E 60
-STATISTICS* SOURCE STATEMENTS = 298.PROGRAM SIZE = 9234
-STATISTICPS NO DIAGNOSTICS GENERATED
```



-GPTIONS IN EFFECT* ID.EECDIC,SOURCE.NOLIST,NODECK.LOAD,NOMAP
 -STATISTICS* NO DIAGNOSTICS GENERATED





|  | C***** USE Massing specs for this ccl to get indexes for checking feasibility |
| :---: | :---: |
| 0162 | Jx=II |
| 0163 | MIJ! = MİJ(Jx) |
| 0164 | : $1 \mathrm{IJZ}=\mathrm{MIIJ}(J \mathrm{X}+\mathrm{MaxCOL})$ |
| 0155 |  |
| 0165 | MIJ23=kIJzatiJ3 |
| 0167 | Mİ3=*IJ23-11IM |
| 0168 | MII2=IIIM+MIJZ <br> SET LP OUTPUT ROUTINE FOR NEW TGT |
| 0169 | IIAM=11 |
| 0170 | MTUC=MIJ |
| 0.71 | M12C=*!J2 |
| 0172 | 12=1 |
| 0173 | DC $150 \mathrm{I}=111 \mathrm{MIIT}$ |
| 0174 | MPUVEC(I2)EIABS(MSIJ(I)) |
| 0175 | 12=:2+1 |
| 0176 | 150 continue |
| 0177 | TCODE $=1$ |
| 0178 | C*E日** CALL OUTPUT MEAX COVERAGE FOUND SO FAR FOR MASS TGTS |
| 0179 |  |
| 0180 | ITHS $\mathrm{XN}_{\text {S }}=-10$ |
|  |  |
|  | c |
|  | C CONTPDL IS RETURNED TO STATEMENT 2011 WITH MIJI=1 IF ATTEMPTINE TO C TRY ANOTHER PERIOD LENGTH FOR MASSED TARGET WITH ONLY START OR STOP SPEC |
|  |  |
|  |  |
|  | C <br> C**** GET STAM $\&$ STOP TIMES (IF ANY) FOR THIS TGT, CLEAR COLNTERS ANO C**** FLAGS IF MASSING WANTED (OTHERWISE GO DO SINGLE UNIT ASSIGAMENT). |
| 0181 | 2011 SPSTT=SPSTRT(II) |
| 0182 | SPSTP=SPSTOP(II) |
| 0183 | IFMMJj.EG.l)GO TO 203 |
| 0184 | IUCHK ${ }^{\text {a }}$ =0 |
| 0185 | WASSER=S |
| © 158 | NAVP4 $=0$ |
| 0157 | MASFLT $=0$ |
| 0188 | SUMCOV $=0$. |
| 0189 | AVAMIN $=9999$. |
| 0190 | A VAMAX $=0$. |
|  | C**** POINTEFS CLEARED IN FOL DU-LOOP ARE USED TO KEEP UP WITH WHEPE A GAP |
|  | C***** STARTS AND ENCS IN A UNITIS SCHEDULE (IUSFLG, IUEFLC.IUFGMS.IUFGME) |
|  | C**** INDEXES TO CORRESPONDING ROWS (FUZES) RAEE KEPT IN IUFFLG AND IUMFLG. |
|  | C***** IUSFLG.IUEFLG, AND IUFFLG ARE PERMANENT \#ITHIN DO-LOOP STARTING AY |
|  | Co*** STATENENT 203; OTHERS ARE TEMPORARY. |
|  | CH**t ALSO, IUNITF is USEO TO KEED 2 ROWS FROM SAME UNIT FROM BEING MASSED cesen together on the same tgt. |
| 0191 | $002021=1.1$ IGMax |
| 0192 | IFIITMSXN.GT.(-5)) 60 TO 2022 |
| 0193 | IUSFLS(I) $=0$ |
| 0194 | IUEFLG(I)=0 |
| 0195 | IUFFLG(I) $=0$ |
| 0196 | COVRAG(I) $=0$. |
| 0197 | 2022 IUFGMS(I)=0 |
| 0198 | ILFGME (I) $=0$ |






```
8. IF ONE END OF PERICD IS UNSPECID, A RECORD IS KEPT OF ALL UNITS HAYIPG TIME TO GET OFF AT LEAST ONE VOLLEY. THIS IS DONE BY SETTING UP A OUMM PERIUNES UITH A SE OR 3 IN INFSII FOR FUETHER PROCESSINGV
```

c

```
c
**O.: UNLESS A RUN FROM THIS UNIT WAS ALREADY TRIED, SET POINTER TO THIS GAP.
**O.: UNLESS A RUN FROM THIS UNIT WAS ALREADY TRIED, SET POINTER TO THIS GAP.
    IF(IUNITF(IGXX).NE.0)GO TO 450
    IF(IUNITF(IGXX).NE.0)GO TO 450
        UEFLG(IGXX)=1FRS:
        UEFLG(IGXX)=1FRS:
        FFSPSTT.GT.9990.)60 TO 285
        FFSPSTT.GT.9990.)60 TO 285
        EOTH START AND STOP SPECiO -- ALLCK FOR SETUP TINE AND SET FLAG.
        EOTH START AND STOP SPECiO -- ALLCK FOR SETUP TINE AND SET FLAG.
        SPSTX=SPSTT-SUI
        SPSTX=SPSTT-SUI
        - T0 287
        - T0 287
        TOOC=-SU
        TOOC=-SU
        SPSTX \(=\) SPSTP-SUI
        SPSTX \(=\) SPSTP-SUI
        INFSII=3
        INFSII=3
        STARTC FTIME
        STARTC FTIME
        SPSTP = SPSTI
        SPSTP = SPSTI
        -STRTI =NSTARTIIGXX
        -STRTI =NSTARTIIGXX
        STPG=NSTRTI +1
        STPG=NSTRTI +1
        FRST \(=0\)
        FRST \(=0\)
        (1)
        (1)
        \(+16 x x\)
        \(+16 x x\)
        NRIVSA=R:SRAVK (IVSA)
        NRIVSA=R:SRAVK (IVSA)
        FRSTAATC.GT.SPSTF:GO YO 274
        FRSTAATC.GT.SPSTF:GO YO 274
        FROLA: 1 RRST
        FROLA: 1 RRST
        FIIFRST EROMSA.10001
        FIIFRST EROMSA.10001
        0 TO
        0 TO
        IF 1 TPAEV EO 1000
        IF 1 TPAEV EO 1000
            IVSP=(IDREV-1) MAXROW+1GXX
            IVSP=(IDREV-1) MAXROW+1GXX
            FISTOPC.GT.CPSTXJGO TO 450
            FISTOPC.GT.CPSTXJGO TO 450
            TUSELG \((1\) GXX) \(=\) IPREV
            TUSELG \((1\) GXX) \(=\) IPREV
        GO ro 273
        GO ro 273
        IF (STCPC.GT. SPSTX)GO TO 450
        IF (STCPC.GT. SPSTX)GO TO 450
        MASSER=MASSEF: 1
        MASSER=MASSEF: 1
        UNITF (IGXx) \(=16 \times\)
        UNITF (IGXx) \(=16 \times\)
        UEFLG(IGXX)=IFRST
        UEFLG(IGXX)=IFRST
        FOR ONE END GNSPECID
        FOR ONE END GNSPECID
        INDEXES TO CORRESP UNITS, COUNT UNITS WHOSE AVAIL TIME EXCEEDS THASMX.
        INDEXES TO CORRESP UNITS, COUNT UNITS WHOSE AVAIL TIME EXCEEDS THASMX.
        FINFSII.EO. 3)AVAILT=STARTC-SPST
        FINFSII.EO. 3)AVAILT=STARTC-SPST
        IF(AVAILT.GE.AVAMIN) 60 TO 276
        IF(AVAILT.GE.AVAMIN) 60 TO 276



CeEee＊SCHED BY CHECKING OTHER ROW•S SCHEDS FOD COMDATISILITY WITH THE
Ce日ent START／STOP TIMES THAT WOULD RESULT IF THE ENGAGELFNT REGAN AS EARLY
Ce日＊＊IN THE GAP AS POSSIALE ANO LASTEO AS LONG AS THE SLOWEST DRIMARY UNIT
C＊E＊＊TION HAS ALREACY BEFN CALCILATED IN THE COLOOD ENOING IN STATEMENT 201
C＊＊＊＊AND IS CALLED TMAS＊X．ASGNT IS MACE IN THE FIFST GAD WMERE a＂PERFECT
C＊＊＊＊MASS＂WILL FIT．IF NO SUCH GAF IS FOUND：ASTMT IS MADE IN YHE GAP
Ce＊ot WHERE THE MOST PRIMARY UNITS ARE AVAILAPLE．PRCVIDED ENCUGH SECONDARY
C＊＊E＊UNITS ARE AVAILABLE，OR PRIMARY UNITS CAN SE＂STRETCHED＂OR＂SPEEDED
C＊＊＊＊UP＂TO COVER THE TARGET ADEGUATELY．IF THAT DOESN．Y YORK，A NEW VALUE
Cee日e＊IS PUT IN TMASMX WHICH IS CLOSER TO TMASHN，WITH SUCCESSIVELY SHORTER
Cetee．LENGTHS BEING TFIED UNTIL ONE MORKS OR TMASMN IS REACHED．
C＊＊＊
（SEE COMMENTS BETWEEN STATEMENTS 475 ANO 476．）
37C IFIIUNITF（IGXX），NE．0）GO TO 450 INFSII＝5
PERIOO＝SUI\＆TMASMX
IF NOSRTI．GT．0）GO TO 375
CHEAH NONE ASSIGNED：STARY TRIAL PERIOD AS EARLY AS POSSIBLE SPSTTX \(=0\) ．
SPSTX \(=\) SUI SPSTPX＝TMASMX 60 TO 390
375 IFRST＝NFIRST（IGXX） OLDSTP＝－SU！
380 IVSA＝（IFRST－1）＊MAXROW•IGXX
STARTC＝STARTS（IVSA）
NRIVSA＝NSFANK（IVSA） SLOT＝STARTC－OLOSTP IF（SLOT．LT．PERIOD）GO TO 385
383 SPSTX＝OLOSTP
SPSTFX \(=\) SPSTXXPPERIOD
SPSTTX \(=\) OLOSTP + SUI GO TO \(39 n\)
385 OLOSTP＝STODS（IVSA） IFROLD＝IFRST
386 IFRST＝MOO（NRIVSA． 1000 ） IFIIFRST．NE．OIGO TO 380
END OF UNITIS SCHED
SLOTITIME－OLDSTP
IF（SLOT．LT．PERIOD）GO TO 450
Coo＊＊CHECK IF GAP WILL FIT INTO ENOUGH OTHER UNITS，SCHEDS．LOGIC IS
G＊＊＊＊SIMILAR TO SECTIONS STARTING AT STATEMENTS 203 AND 270.
390 DO 3391 LL×1，IGMAX
IUFGMS（LL）\(=0\)
IUFGME（LL）\(=0\)
\(\operatorname{COVERM}(L L)=0\)
IUNF2（LL）\(=0\)
3391
CONTINUE
SUMCOV \(=0{ }^{\circ}\)
MASSER
MASSER \(=0\)
NPRIM \(=0\)
NPRMAX \(=-1\)
DO 410 LL＝IIIPMI23
MSIJXX＝MSTJ（LL）
IFIMSIJXX．LT．O）60 TO 410







\begin{tabular}{|c|c|c|c|c|c|}
\hline FORTRAN I & Iv e i.evel & 21 VOEGLN & DATE \(=78295\) & 12/29/12 & Page cozo \\
\hline 0788 & & covragi i imatiom & & & \\
\hline 0789 & 495 & continue & & & \\
\hline 0790 & & IFIINFSII.EQ.2)SPSTTISPSTP-TLNGTH & & & \\
\hline 0791 & & IFIINFSII.EQ.3)SPSTP=SPSTP + TLNGTH & & & \\
\hline 0792 & & TMASMX =TLNGTH & & & \\
\hline 0793 & & 60 TO 452 & & & \\
\hline 0794 & 500 & continue & & & \\
\hline 0795 & 2000 & continue & & & \\
\hline 0796 & & RETURN & & & \\
\hline 0797 & & ENO & & & \\
\hline
\end{tabular}
-OPTIONS IN EFFECT* ID,ESCDIC,SOURCE,NOLIST, NODECK, LOAD, NOMAP
OPTIONS IN EFFECT* NAME \(=\) VOEGLN , LINECNT \(=\) 60
sIze
-STATISTICS* NO DIAGNOSTILS GENERATED
```

fortran iv g level 2l
SURROUTINE SORTER

$0001 \quad$| $c$ |  |
| :---: | :---: |
|  | $c$ |
|  | $c$ |
|  | $c$ |
|  | $c$ |
|  | $c$ |
|  | $c$ |

-OPTIONS IN EFFECT* ID,EBCOIC,SOURCE,NOLIST,NODECK.LOAD,NOMAP -OPTIONS IN EFFECT NAME $=$ SORTER , LINECNT = 60 SOURCE STATEMENTS $=$ 33.PRCGRAM SIZE = 776





```
fortran iv g level 2l
CMART
12 CONTINUE
11 CONTINUE
10 CONTINUE
PRIAT 2C, (IG(J),JIIoNU)
```



```
print 30
```



``` PRINT \(40,(J, J=1, N U)\)
40 FCDNAT(8x.4113)
DRTHT 45
45 EOEMAT( TIMED)
C PRINT CHART LIPES ONLY AFTER FIRST ENGAGEMENT REGINS a BEFORE LAST ONE ENDS. 0060 I=ISMIN.ISMAX
DPI\&T 5O,CTIME, (ICMART (J,I), JEI, NU)
50 FCRMET(F5.1.3X.41(1 1,12))
CTIME=CTIME TINC
60 CONTINUE
PETU
END
-DDTIONS IN EFFECTY ID.EECDIC,SOURCE,NOLIST,NODECK.LOAD,NOMAP COTIOVS IN EFFECT NAME = CHART, LINECNT I
STATISTICS SCURCE STATEMENTS = GI, PROGRAM SIZE = 17728
-STATISTICS NO DIAGNOSTICS GENERATED
-STATISTICS* OOZ DIAGNOSTICS THIS STEP
```

APPENDIX F

OUTPUT SAMPLES FROM PROGRAM IN APPENDIX E

##  <br> - SumMARY of input data <br> 



```
ROW NO.: 2- % % % 5
AMMO SUPPLY VECTOR: 638. 246. 478.
VECTOR OF TIMES (MIN) FOR SETUP & FIRST ROUND:
VECTOR OF TIMES (MIN) PER ROUND (SUSTAINED FIRE):
    0.400 0.050 0.100 0.100 0.500
VECTOR OF NO. TUBES PFR ROW: 6. 6. 1. 6. 1.
VICTOR OF UNIT GROUP NUMBERS: 
```

| HAECECENCE 1 TARGETS: | 1 | 2 |  |
| :--- | :--- | :--- | :--- | :--- |
| PRECEDENCE 2 TARGETS: | 3 |  |  |
| PRECFDENCE 3 TARGETS: | 4 |  |  |
| PRECEDENCE 4 TARGETS: | 5 |  |  |
| PRECFDFNCE 5 TARGFTS: | 6 | 7 | 8 |
| PRECFDENCE 6 TARGETS: | 9 |  |  |
| PRECEDENCE 7 TARAETS: | 10 |  |  |

MASSING INFOHNATION:

| TGT | NO. UNITS | ROWS TO RE CONSIDERED: |
| :--- | :---: | :--- | :--- | :--- | :--- | :--- |
| NO. | TO MASS | COTHERS HAVE BEEN FLAGGED INFEASIBLES |

## START-STOP INFORMATION 19999 . NOT SPECYFIED)

TARGET START TIME STOP TIME

| 1 | 4.000 | 16.000 |
| ---: | ---: | ---: |
| 2 | 9999.000 | 20.000 |
|  | 8.000 | 9999.000 |



SUM OF COLUMN COST MINIMA: 322.00

MATRIX OF ENGAGEMENT TIMES:
(NOTE NEW INFEASIBILITIES DUE TO MASSING. TIME, OR AMMO)
ROW:

| 1: | 4.000 | 5.600 | 3.200 | 3.200 | 5.600 | 4.000 | 4.800 | ***** | 8.400 | 4.000 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 2: | 3.600 | 5.650 | 3.550 | 2.350 | 2.400 | 4.400 | 2.850 | 1.650 | 1.500 | 1.300 |
| 3: | 1.000 | -wa**** | 2.000 | 1.200 | 1.300 | 1.900 | -****** | 1.900 | 1.600 | 2.4 |
| 41 | 1.900 | -***** | -cost** | 1.500 | 2.300 | 1.700 | 2.400 | 2.500 | 1.700 | 2.3 |
| 58 | **** | 23.000 | 32.500 | 23.000 | 26.000 | ***** | 12.000 | -****** | - | 7.500 |

H(= 255.591)-WEIGHTED MAX:R/A.E/T)-MATRIX:
ROW:




RESULTS FOR ALPHA $=0.25000$

```
        UNIT ROW FRACTION SHELLS START STOP SETUP SOST
        llllllll
    ASGMT FOD TGT 2: NO. UNITS OESIRED: 2: PRINARY ROWS: 2 1
    UNIT ROW FRACTION SHELLS START STOP SETUP COST
    ** UNASSIGNED
    ASGMT FOR TGT 3: NO, UNITS OESIRED: 2; PRIMARY RONS: l 3 5 6
    UNIT ROK FRACTION SHELLS START STOP SETUD COST
    lrrrrrrererern
    ASGMT FOR TGT ABNO. UNITS DESIRED: IS PRIMARY ROWS: 2 & SACTION SWELLS START STOP SETUP COST \ 3
    NIT ROW FAACTION SKELLS START STOP
    ASGMT FOR TGT 5: NO. UNITS DESIRED: 1: PRIMAFY ROWS: 4 2 5 1 3
    UNIT ROW FFACTION SHELLS START STCP SETUP COST
    ASGMT FOR TGT 8& NO. UNITS DESIRED: IF PRIMARY ROWS: 3 4 a
    UNIT ROW FRACTION SHELLS START STOP SETUP COST
    ASGMT FOR TET 6: NO. UNITS DESIRED: I: PRIMARY ROWS: & 1 2 3
    UNIT RON FRACTION SHELLS STAET STOP SETUP COST
    ASENT FOR TGT T: NO. UNITS DESIRED: 1% PRIMARY ROKS: 5 i 2 l
    ASENT FOR TGT T: NO. UNITS OESIRED: I% PRIMARY ROKS:
    3 4 1.000000 SHELLS S0. 20.30 22.70 1.00 19.CO
```



```
    ASGMT FOR TGT 10: NO. UNIITS DESIRED: 1% FRIMARY ROKS: 1 3 4 5 2
    UNIT ROW FRACTION SHELLS START STOP SETUP COST
    1 1 1.000000 34. -2.00 2.00 2.00 10.00
```

    ASSIGNMENT SUMMARY
    NO. TGTS PRESENT WAS 10, NC. TGTS ASGD WAS 9. NO. TGTS UNASGD WAS 1
    NO. TGTS ASGD TO SECENDARY ROWS WAS O
    no. TGTS WITH UNEVEN COVERAGE WAS \({ }^{\circ}\)
    $\checkmark \quad$ NO. TGTS WITH WRONG NO. UNITS MASSEO wAS o

| SCHEDULE OF FIRING ASSIGNMENTS: |  |  |  |  |  |  |  | *** |  | UNITS |  | $4{ }^{* * *}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| UNIT |  |  |  |  |  |  |  | 1 | 2 | 3 | 3 |  |
|  |  |  |  |  |  | - ${ }^{\text {a }}$ |  |  |  |  |  |  |
| 1 | START | Step | tot | ROW | SHELLS |  |  | 1 | 2 | $R$ 3 | - | 5 |
|  | -2.00 | 2.00 | 10 | 1 | 34 | - | time |  |  |  |  |  |
|  | 2.00 | 16.00 | : | 1 | 12 |  | -2.0 | 10 | 0 | 0 | 0 | 0 |
|  | 16.90 | 18.40 | 3 | 1 | 11 |  | -1.0 | 10 | 9 | * | 5 | 0 |
|  | SLaCk | TIME: | 9.600311 |  |  | - | 0.0 | 10 | 9 | ** | 5 | 0 |
|  | SLack | АलMO IN | ROW | 115 | 57. Sheills |  | 1.0 | 10 | 9 | ** | 6 | 0 |
| 2 |  |  |  |  |  |  | 2.0 | 10 | 0 | ** | 6 | 0 |
|  | START | STOP | TGT | ROW | Shells | $\cdots$ | 3.0 | 1 | 1 | ** | 6 | 0 |
|  | -1.00 | 0.50 | 9 | 2 | 11 |  | 4.0 | 1 | 1 | ** |  | 0 |
|  | 3.00 | 16.00 | 15.500 2 13 |  |  |  | 5.0 | 1 | 1 | ** | 1 | 0 |
|  | SLACK | TIME: |  |  |  | .- | 6.0 |  | 1 | ** |  | 4 |
|  | SLACK | AMMO IN | ROW 2 | 2 IS | 565. SHELLS |  | 7.0 | 1 | 1 | ** | 1 | 4 |
| 3 |  |  |  |  | SHELLS | - | 6.0 | 1 | 1 | - | 1 | 4 |
|  | $\begin{aligned} & \text { START } \\ & \text { - } 1.00 \end{aligned}$ | STOP 1.30 | TGT | ROW | SHELLS |  | 9.0 | 1 | 1 | -* | 1 | 4 |
|  | 1.30 | 3.00 | 6 | 4 | 45 | ; . ${ }^{\text {i }}$ | 10.0 11.0 | 1 | 1 | ** | 1 | 4 |
|  | 3.00 | 16.00 | 1 | 4 | 19 | - | 12.0 | i | 1 | ** | 1 | 4 |
|  | 17.00 | 18.40 | 3 | 3 | 32 | $\because$ | 13.0 | 1 | 1 | -* | 1 | 4 |
|  | 18.40 | 20.30 | 8 | 3 | 55 |  | 14.0 | 1 | 1 | ** | 1 | 4 |
|  | 20.30 | 22.70 | 7 | 4 | 90 |  | 15.0 | 1 | 1 | ** | 1 | 4 |
|  | SLACK | TIME: | 7.3003 |  |  |  | 15.0 | 3 | 1 | - | 1 | 4 |
|  | SLACK | AMMO IN | $\begin{aligned} & \text { ROW } \\ & \text { ROW } \end{aligned}$ | $\begin{aligned} & 3 \text { IS } \\ & 4 \text { IS } \end{aligned}$ | 551. SHFLLS |  | 17.0 | 3 | 0 | 3 | ** | 4 |
|  | SLACK | AMMO IN |  |  | 9. SMELLS |  | 18.0 | 3 | 0 | 8 | -* | 4 |
| 4 |  |  | $\begin{aligned} & \text { TGT } \\ & 7.0003 \\ & \text { ROW } \end{aligned}$ | $\begin{array}{r} \text { ROH } \\ 5 \\ 5 \text { IS } \end{array}$ |  | - | 19.0 | 0 | 0 | 8 | * | 4 |
|  | START | STOP |  |  | Shells |  | 20.0 | 0 | 0 | ** | 7 | 4 |
|  | 6.00 | 29.00 |  |  | $43$ |  | 21.0 | 0 | 0 | ** | 7 | 4 |
|  | SLACK | TIME: |  |  |  | - | 22.0 | 0 | 0 | ** | 7 | 4 |
|  | SLACK | AMMO IN |  |  | 435. SHELLS |  | 23.0 | 0 | 0 | ** | 7 | 4 |
|  |  |  |  |  |  |  | 24.0 | 0 | 0 | 0 | 0 | 4 |
|  |  |  |  |  |  |  | 25.0 | 0 | 0 | 0 | 0 | 4 |
|  |  |  |  |  |  |  | 26.0 | 0 | 0 | 0 | 0 | 4 |
|  |  |  |  |  |  |  | 27.0 | 0 | 0 | 0 | 0 | 4 |
|  |  |  |  |  |  | - | 28.0 29.0 | 0 | 0 | 0 | 0 | 4 |

## PESULTS FOR ALPHA $=1.00000$ :




VITA 2

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Thesis: HEURISTIC SOLUTION METHODS FOR MULTI-RESOURCE GENERALIZED ASSIGNMENT PROBLEMS

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