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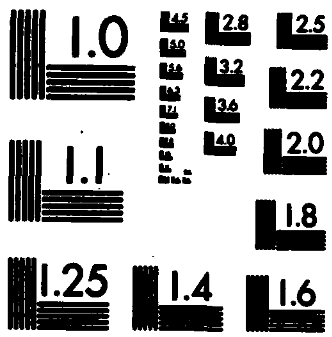

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Monterey, California

THESIS

DESIGN AND SOLUTION OF AN AMMUNITION DISTRIBUTION MODEL BY A RESOURCE-DIRECTIVE MULTICOMMODITY NETWORK FLOW ALGORITHM

by

Cyrus James Staniec

September 1984

Thesis Advisor: Gerald G. Brown

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Planning distribution of multiple commodities in a capacitated network is a problem frequently encountered in civilian and military logistic systems. However, application of optimization to large-scale problems has been limited. Specialized solution techniques for the multicommodity transhipment problem (MCTP) have emerged in recent years which improve solution efficiency, but have been used only on relatively small models.

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Design and Solution of an Ammunition Distribution Model by a Resource-Directive Multicommodity Network Flow Algorithm

by

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ABSTRACT

Planning distribution of multiple commodities in a capacitated network is a problem frequently encountered in civilian and military logistic systems. However, application of optimization to large-scale problems has been limited. Specialized solution techniques for the multicommodity transhipment problem (MCTP) have emerged in recent years which improve solution efficiency, but have been used only on relatively small models. This effort documents the use of a resource-directive network optimization algorithm, MNET, to solve a large-scale MCTP. An ammunition distribution system is modelled with up to 100 commodities, over 300,000 constraints, and 1,000,000 variables. A feasible solution of excellent quality is produced in minutes by MNET. MNET is designed to solve completely general MCTP and may be applied directly to other problems of this broad class.

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I. INTRODUCTION

Planning transhipments through a capacitated distribution network is a continuing problem in both civilian and military logistics systems. When a single commodity is involved, even large problems may be solved optimally using any of a number of specialized algorithms which exploit the pure network structure of the problem (see, for example, Bradley, Brown, and Graves [Ref. 1] or Glover, Karney, and Klingman [Ref. 2]). However, when several distinct commodities share the transportation links of the network, the commodities are bound together by the presence of joint capacity constraints on transportation links, preventing pure network algorithms from being applied directly. In the absence of specialized solution technology, the size of the constraint matrix grows rapidly with the number of products, demanding increased solution effort.

Because of its frequent occurrence, the MCTP has been widely studied and methods have been developed which exploit the underlying structure of the problem in ways which reduce the solution effort. Surveys by Assad [Ref. 3] and Kennington [Ref. 4] categorize these methods under the major headings of price-directive decomposition, resource-directive approaches, partitioning, and compact inverse methods.

Computational work by Ali, Helgason, Kennington, and Lall [Ref. 5] suggests that a resource-directive subgradient optimization method is the fastest of the methods listed. In the resource-directive approach, the MCTP is broken into a non-network master problem and independent single-commodity network subproblems by allocating capacity from the joint constraints to each commodity, which may then be solved using a specialized network algorithm. The Ali et al. report presents results in which multicommodity problems on the order of 1000 constraints and 2300 variables were solved in times ranging from a few seconds for the simplest to a few minutes for the most difficult.

Although such results are encouraging, the size of most distribution problems is considerably larger, and there is no evidence in the open literature of validation of these solution techniques at large-scale. The aim of this investigation is to formulate a multicommodity optimization model of a large scale distribution system of interest to the Army and to test the performance of a resource-directive optimization procedure in solving the resulting problem.

The problem under study is the ammunition distribution problem faced by the US Army Armament, Munitions, and Chemical Command (AMCCOM). As the Single Manager for Conventional Ammunition (SMCA) for the Department of Defence, AMCCOM is responsible for production, supply, maintenance, and distribution of conventional ammunition for the US armed services. AMCCOM owns and operates a large network of production facilities, or ammunition plants, at which the Army produces, loads, assembles, and packs most of the explosive ordnance used by the military, ranging from blasting caps and small arms ammunition to large projectiles and aircraft bombs, which are collectively referred to as conventional munitions. Excluded are specialty items such as missiles and torpedoes. AMCCOM also manages the flow of ammunition within the United States to air and sea ports for shipment to overseas locations.

This ammunition distribution system is constantly used at a moderate rate to meet military needs for ammunition during peacetime. However, during periods of military threat or actual conflict, the system will mobilize to meet the ammunition demands of US forces. Upon mobilization, large quantities of ammunition will be shipped from storage depots to field locations to sustain the first critical days of combat. After this initial "surge" provides in-theater stockpiles, the activity will diminish somewhat from its peak to provide ammunition to the field at rates suitable for sustained combat. At the same time, production will increase as production lines expand and "mothballed" plants re-open to meet the continuing need for ammunition.

The model of the physical ammunition distribution system developed in this study is a planning model which determines optimal flows to fill time-phased demands for ammunition as presented in mobilization contingency plans. Data for the model is drawn from the database for the AMCCOM Ammunition Distribution System (ADS), which is a series of simulation models currently used to assist in planning for mobilization, to assess plans, and to provide operational assistance for mobilization exercises [Ref. 6]. The ADS system was developed and put in production in 1981 after a previous optimization model using linear programming proved to be too slow to meet the users' needs.

Successful solution of the prototype ammunition distribution model formulated in this study does more than demonstrate the advantages of using new solution technology; it provides an improved planning tool for use in this and in other production/distribution problems. As a planning model, it does not compete with an existing tool such as ADS, but complements it. When used in an iterative fashion, emphasizing the strengths of both the optimization and the simulation, the results provide more insight into the physical system than either method individually. Examples of this iterative process are described by House and Karrenbauer in their paper on logistic modelling [Ref. 7].

The result of this investigation is a demonstration that large logistic planning problems such as AMCCOM's ammunition distribution problem may now be routinely and reliably solved with acceptable resolution and computational cost using specialized solution technology. A prototype multicommodity ammunition distribution model is documented and efficiently solved using a resource-directive multicommodity network flow algorithm. The algorithm, MNET, developed by Professor Richard Rosenthal of the University of Tennessee is tested with a series of small test problems. Computational results for production-scale problems containing up to 100 commodities are presented, and conclusions are drawn both about the performance of the instance of the distribution model studied here and about the performance of MNET. Although much of the paper is devoted to developing the particular ammunition distribution model, the MCTP is general enough so that the results of this study may be extended directly to other similar distribution problems.

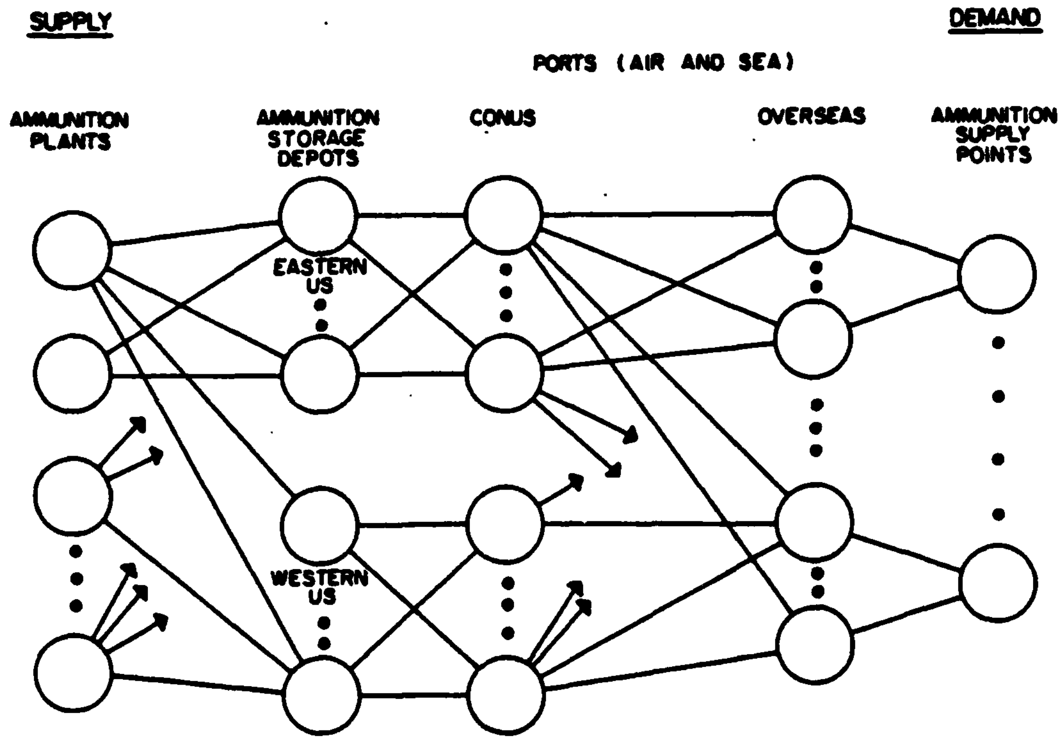
II. PHYSICAL SYSTEM

The ammunition supply system managed by AMCCOM operates at the wholesale level, distributing nearly 700 end items to meet the aggregate demands for each of the armed services in theatres of operations around the world. Broadly speaking, the system may be described in terms of the distribution network itself and the functional considerations which govern its operations. The following description of the system is derived from AMCCOM Technical Report TR 10-81 [Ref. 6] and interviews with AMCCOM analysts responsible for designing the current ADS system.

A. THE NETWORK

The spatial layout of the distribution system as described in TR 10-81 is shown in Figure 1.

Assets are produced and stored at approximately 35 plants and depots which are located throughout the continental US (CONUS). Each particular item is produced in one or more locations and stored at a number of depots ranging from one for low-demand items to ten or more for high-demand items. During peacetime, the operation of the plant and depot echelons is relatively stable and production tends to enter the system at a relatively low rate. However, when conflict is imminent, the system mobilizes, production quotas increase and mothballed plants and production lines are reopened so production occurs in larger quantities at more locations over time. Frequently there is a significant time lag between the onset of mobilization and the point when increased production begins to enter the distribution system.



AMMUNITION DISTRIBUTION NETWORK
Figure 1.

Demands for ammunition originate at ammunition supply points in CONUS and overseas. Each requisition specifies a required delivery date. In order to meet the demands, ammunition is shipped from the plants and depots to the appropriate CONUS location or port for delivery.

Transportation among the plants and depots and to CONUS ports of embarkation is managed by AMCCOM using civilian road and rail resources. The generally preferred mode of transportation within CONUS is rail due to larger shipping capacities and lower shipping costs, but road movement frequently is faster.

Distribution to destinations outside of CONUS may be accomplished either by sea or air shipment. Sea shipment is preferred due to the ability to ship large tonnages, but air shipment is the only way in which many short lead-time requirements can be met. Typically air transport is accomplished in one day, while sea travel may require two to four weeks from port of embarkation to port of debarkation plus in-port handling time. Again, the preferred mode is also much cheaper.

Each plant or depot is usually served by only one nearby airport of embarkation (APOE), although each airport may serve several depots. Prior to mobilization, there are normally three CONUS seaports (SPOE) available for outloading of ammunition. This number increases during mobilization, usually with a lag time before the extra ports are available. These seaports are categorized by the number of berths available and by their ability to handle containerized and break-bulk cargo, which affects the amount and packaging of ammunition handled by each port. Generally east-coast ports serve only plants and depots in the eastern half of the United States and western ports serve only the western half.

The number and locations of overseas ports vary widely depending on the situation. In peacetime there are established airports and seaports serving geographic locations where large US contingents are present. During mobilization the location, number and types of ports will be highly dependent on the region in which US military involvement is to take place. Furthermore, some of the ports may not become operational until US forces have had an opportunity to establish secure positions in the region of interest. In such cases, either air or sea lock dates may be established, which represent the earliest date on which ammunition may be scheduled to arrive at that port.

Usually each airport of debarkation (APOD) will serve only one geographic location (GLOC) within the region of interest, while a seaport of debarkation (SPOD) may serve multiple geographic locations.

The function of the plants and depots is to provide adequate supplies of each item requested to meet the time-phased demands at each of the geographic locations. Physically, the ability to distribute ammunition to meet demands within this network is limited when any of the following conditions occurs:

1. There is an insufficient supply of one or more items to meet requirements;

2. The available capacity of some mode of transportation at a given time is inadequate; or

3. The material handling capacity of some plant, depot, or port is insufficient.

During mobilization, and especially during the early response period, the system tends to become saturated. For ammunition system managers the problem is to determine shipment schedules that minimize the shortfall in deliveries or the backlogging time incurred. This distribution system is documented by a detailed administrative reporting system which keeps track of the status of every requisition and shipment made.

B. OPERATIONAL CONSIDERATIONS

Movement of ammunition through the physical network must comply with many operational and administrative considerations, the most important of which are discussed here.

First, some timeliness restrictions are employed during mobilization to ensure that ammunition is not shipped to arrive too early or too late. This rule will be considered later in terms of a desired "delivery window" incorporated in the prototype model.

Items are usually requisitioned in units of each. However, since the system operates at the wholesale level, shipments are made in unit pack or pallet configurations.

Quantities requisitioned in other than multiples of unit packs or pallets are rounded up to the next higher incremental unit pack.

Most locations other than the depots have limited holding capabilities. Therefore, shipments must be received at a port, for instance, as close to the departure time from that location as possible.

When aggregated for shipment, items shipped must satisfy several physical as well as safety constraints. All modes of transportation are limited by weight and volume that can be carried. In addition, restrictions exist on the amounts of net explosive weight (NEW) that can be carried in a shipment.

These operational considerations are addressed in the discussion of the model formulation. Other important considerations have been left out of the prototype model to make the initial model manageable. These considerations will be mentioned in the concluding chapter as areas for future development.

III. AMMUNITION DISTRIBUTION MODEL

This chapter presents the basic mathematical formulation of the multicommodity ammunition distribution system and then discusses the prototype model tested in this investigation. Methods used to represent operational constraints in the model are discussed in detail. The second section of the chapter discusses the software used to generate the network and process output from the solver.

A. MATHEMATICAL FORMULATION

The minimum cost multicommodity transportation problem is formulated as follows:

$$\min \sum_{k \in K} \sum_{j \in A} c_{jk} x_{jk} \qquad (3.1)$$

subject to

$$\sum_{j \in F_i} x_{jk} - \sum_{j \in R_i} x_{jk} = b_{ik}, \text{ all } (i,k) \in (N,K) \qquad (3.2)$$

$$\sum_{k \in K} x_{jk} \le u_j, \text{ all } j \in A \qquad (3.3)$$

$$x_{jk} \ge 0, \text{ all } (j,k) \in (A,K) \qquad (3.4)$$

where K = set of commodities,

N = set of nodes,

A = set of arcs,

(N,K) = Cartesian product of N and K,

(A,K) = Cartesian product of A and K,

x_{jk} = (variable) flow of commodity k on arc j,

c_{jk} = (given) unit cost of flow of commodity k on arc j,

b_{ik} = (given) supply of commodity k at node i,

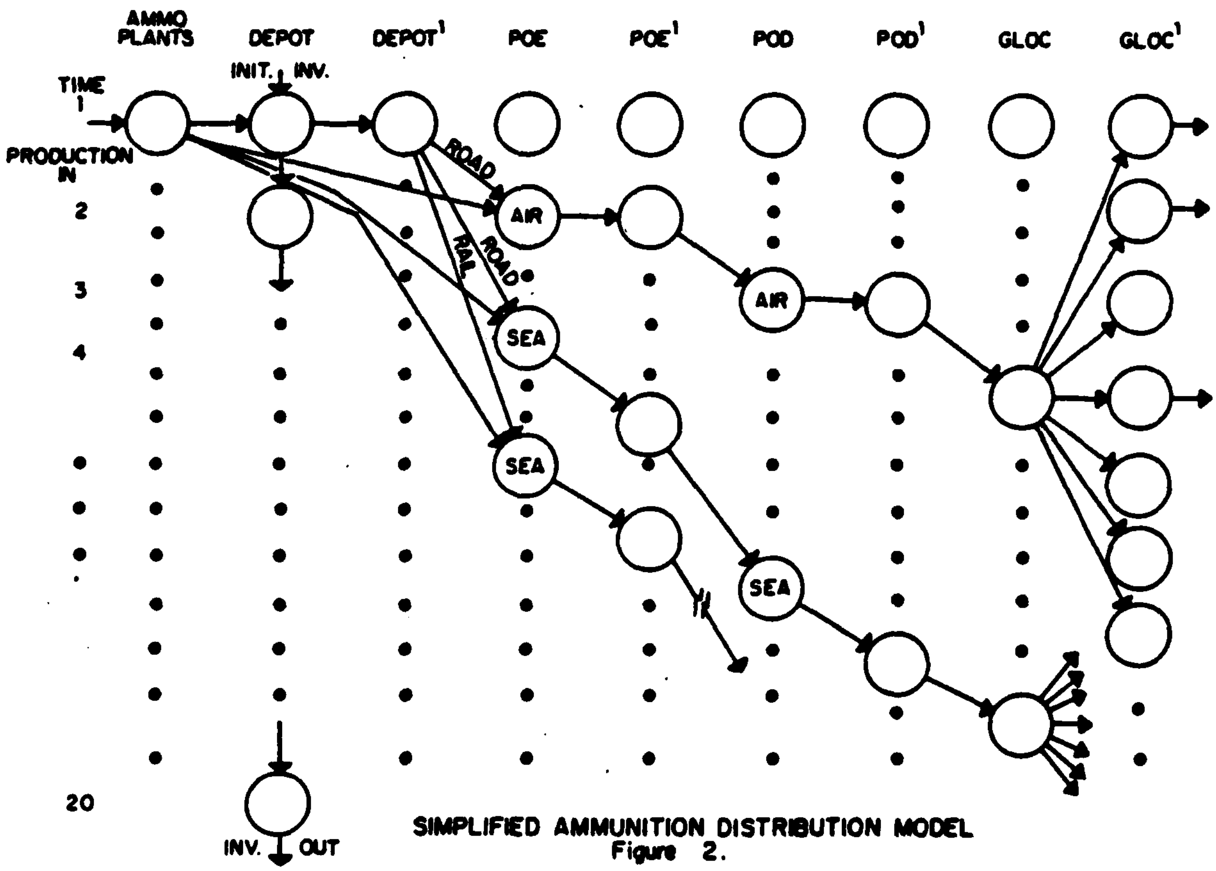
u_j = (given) joint capacity of arc j,

F_i = $(j:(i,j)\epsilon A)$,

R_i = $(j:(j,i)\epsilon A)$.

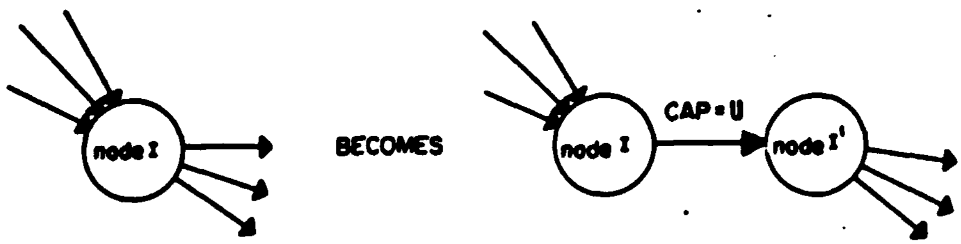
It is assumed that supplies are in balance, i.e., $\Sigma_i b_{ik} = 0$, for all k, or else the flow balance equation (3.2) would be inconsistent. The set of equations (3.2) and (3.4) define a set of disjoint single commodity networks. The set of joint capacity constraints defined by (3.3) ties all of the commodities together in the MCTP.

In the AMCCOM instance, the MCTP is defined in five echelons; plants, depots, POE's, POD's, and GLOC's replicated over T time periods. That is, each node, i, in the model represents a specific location in a specific time period and each arc represents the amount of time required to move between two locations using a particular mode of transportation. Supply $(b_{ik}>0)$ enters the system either as production in the plant echelon or as initial inventory in the depot echelon. From that point, it is either drawn through the network to fill demands at the GLOC's or is carried in the depot echelon as inventory. Demands (b_{ik}<0) are time-phased, occurring at a particular GLOC and time on the horizon of the model. A simplified version of the resulting network is depicted in Figure 2. It shows the possible paths which may be taken by supply of some item entering the network in the first time period.



SIMPLIFIED AMMUNITION DISTRIBUTION MODEL
Figure 2.

Joint flows in the model are currently limited by the throughput capacities at the node locations. In order to accomplish this, each echelon with throughput capacities is represented in the model as two echelons (e.g. Depot and Depot^{1}) and corresponding locations in each echelon are joined by a capacitated throughput arc, as shown in Figure 3 (source: Ford and Fulkerson [Ref. 8]). Using handling data provided by AMCCOM, these capacities are expressed in short tons. In the seaports, throughput is passed forward one time period to compensate for in-port delays.

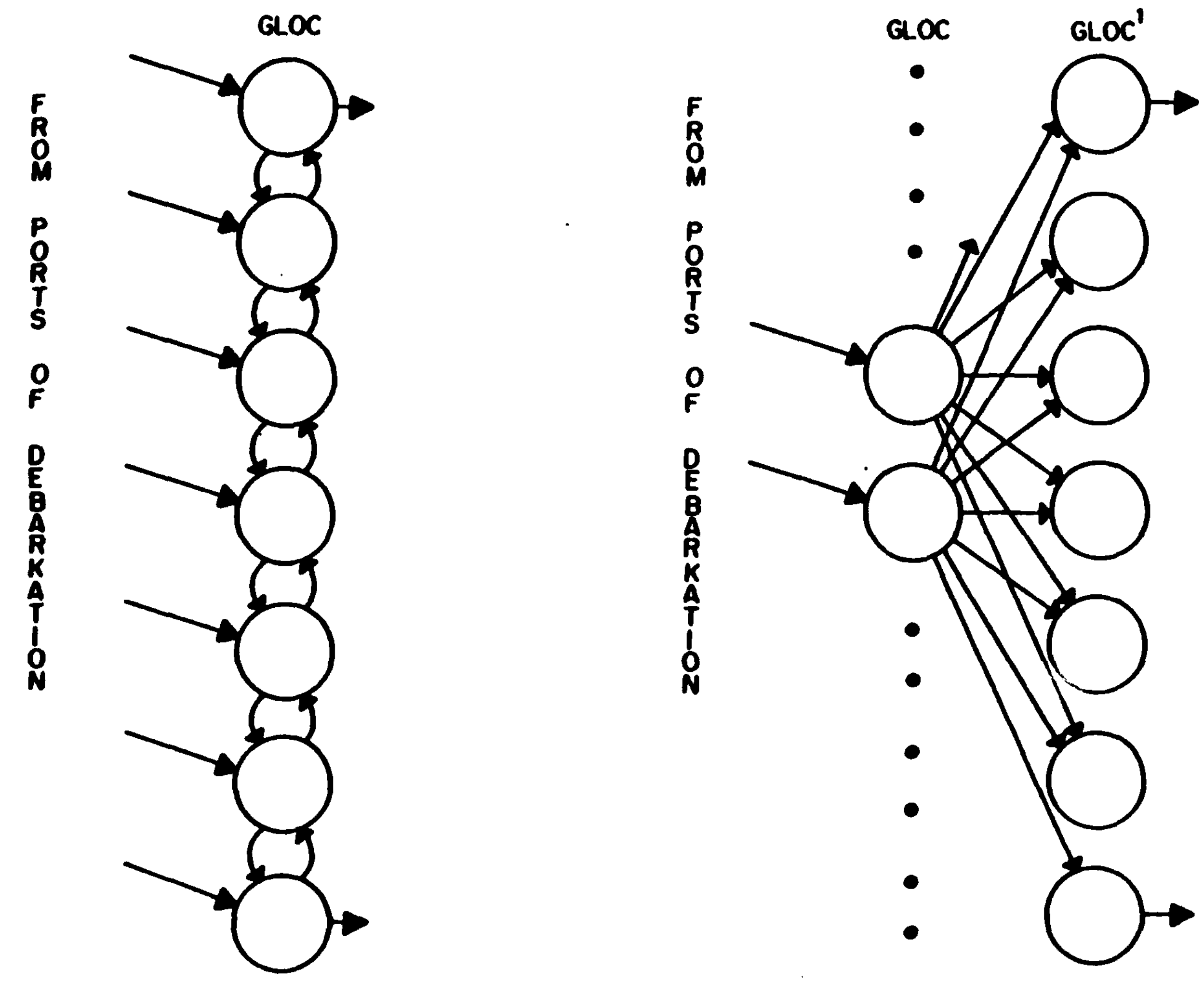


METHOD OF LIMITING THROUGHPUT AT NODE I TO U STONS
Figure 3.

Movement from the plants and depots to the POE's may be accomplished by road or rail. Separate arcs are required for the two modes because the transit times between any two locations are usually different.

The delivery window concept described for the physical system is incorporated in this model as a system of backlogging and early arrival arcs. The prototype model contains two methods of representing the delivery window which are shown in Figure 4. In the simple backlogging representation, each geographic location is connected backward and forward in time to the corresponding location within the same echelon. In the time-limited backlogging representation, a second echelon of geographic locations is produced and explicit arcs are generated which connect arriving flows in the first echelon with the time periods in the second echelon for which they are allowed to fill demands. The time-limited version is also shown in Figure 2. In both cases, a penalty cost is associated with each of the arcs representing an early or late arrival. The penalty cost is relatively small in the case of early arrivals and large for late arrivals, so that the solution algorithm will attempt to make deliveries on time whenever possible, otherwise early, and late only as a last resort. Performance of the two backlogging methods is described in Chapter V.

The objective as stated in equation (3.1) is to minimize the total cost of transporting ammunition through the system. However, the goal of the physical system is to minimize the deviation from on-time deliveries. In order to coerce the MCTP formulation to minimize deviation from on-time deliveries according to some specific shipping policy, the penalty costs must reflect the cost difference between shipping via a slow, inexpensive mode versus a fast, more expensive mode. By properly setting, or tuning,



A. SIMPLE BACKLOGGING B. TIME LIMITED BACKLOGGING

DELIVERY WINDOW REPRESENTATIONS

Figure 4.

the penalty costs, the point in time at which the model will select costly air deliveries over inexpensive sea deliveries can be controlled effectively. This is discussed in detail in Chapter V.

The objective function terms c_{ik} include a priority factor, δ_k, which allows certain designated items to receive shipment priority by multiplying the penalty cost associated with late delivery of those items.

The costs associated with throughput arcs have been set to zero and do not affect the objective function. A study conducted for the Logistics Management Institute indicates that both throughput costs and capacities are important elements in models which address questions such as transportation cost reduction, optimum stockage location, and surge/expansion capability for mobilization [Ref. 9]. However, since this model is currently being used for mobilization evaluations with emphasis on minimizing backlogs and shortfalls, throughput costs may confound the results if there is a large disparity in throughput costs at various locations. Therefore, no attempt has been made to obtain these costs, but they may be easily incorporated to support other types of investigations, if required.

B. NETWORK GENERATION

Two FORTRAN programs, AMNET and AMREPORT, have been developed to efficiently generate instances of the network described by the mathematical formulation. Using data obtained from AMCCOM, AMNET constructs the network and the supplies and demands for each of the commodities. AMREPORT translates numerical output from the optimizer into simple tables of shipping plans by commodity and total flow on each capacitated arc.

The design of the network generator includes the characteristics of (1) compatibility with the input format requirements of the MCTP solver, MNET, (2) flexibility in changing the configuration of the network for different scenarios, and (3) utility in incorporating some of the operational considerations of the physical system into the network structure. The report writer demonstrates the basic techniques that must be included to develop a more formal system.

Each network is generated in a format compatible with GNET, the primal network algorithm used by MNET to solve subproblems [Ref. 1]. The list of arcs in the network is stored in two one-dimensional arrays, H(.) and T(.). For each node, i, in the network, H(i) indicates the location in T(.) which begins the list of arcs which are oriented toward i in the network. Thus, there is an entry in H(.) for every node in the network and an entry in T(.) for every arc. Two additional arc-length arrays, C(.) and CP(.), contain the costs and capacities associated with each arc, respectively.

The prototype distribution network consists of 27 plants and depots, 12 ports of embarkation, 15 ports of debarkation, 13 geographic locations, and 20 three-day time periods. Each type of location forms a different echelon or pair of echelons joined by a throughput arc, and each specific location appears in its echelon once in each time period in the problem. The same underlying network is used for every commodity, so it is generated only once for each multicommodity problem. The scheme used in AMNET completely generates one echelon for all time periods before going to the next echelon, making it easy to calculate the node number of a specific location in a specific time period. For the network described above, for instance, the nodes in the first echelon are numbered 1 through (27x20) = 540.

The connections which are allowed between the plants, depots, and ports in the network are controlled by entries in travel time matrices constructed from data files used in the ADS system. For any connection which is not allowed according to the ADS data, a value greater than the time horizon of the model is listed in the appropriate location in the matrix, and the connection is not constructed by the generator. For each location allowed to ship to a particular head node, the appropriate travel time entry is used to calculate the time period of origin for the resulting arc. The index number of each location and the time period of origin are used in turn to calculate the correct number of the tail node to be entered in the T(.) array. The travel time is also multiplied by a basic shipping cost per day per ton to calculate the cost per ton for flows on that arc. The costs used in the test model are representative costs obtained from AMCCOM. Although the costs are not precise, their relative magnitudes are approximately correct so that solutions obtained will closely resemble those derived with more detailed data. For throughput arcs, the costs are currently set to zero, but can express handling costs.

At present the only capacities in use are the throughput capacities in the depot and port locations. These values are read from a 1-dimensional array for ports, where throughput capacity is primarily a function of the number of berths in the port, or from a 2-dimensional array for plants and depots where the capacity increases over time as more material-handling equipment is added. All CP(.) entries for uncapacitated arcs are set to a suitably large value.

Because the current data includes only thirteen geographic locations which are each connected to a few specific ports, the connections are generated explicitly in AMNET. However, ADS considers a maximum of 150 geographic locations at present. Therefore, the following method is proposed for generating the allowable connections between these echelons in a future enhancement to AMNET. Following the example of the GNET input format, a list of all geographic locations is constructed as a head array, pointing to a tail array which lists the ports that serve each geographic location. A sign bit is used to distinguish seaports from airports. Given a list of specific locations to be included in a problem, AMNET constructs the appropriate POD to GLOC arcs by accessing the head and tail lists at the appropriate locations. The head and tail lists may be maintained as permanent data and only modified when there is a change to the total set of locations considered in the model.

The use of transit time arrays and the method described above for generating geographic location connections instills the network generator with a great deal of flexibility. By simply changing the values of the basic input parameters and including the appropriate values in the transit time matrices, any desired network can be generated, including the addition of new locations or addition of new connections between existing locations. Geographic locations can be modified simply by varying the input list. However, the generator is somewhat inflexible with respect to changes in fundamental network topology; adding new delivery methods may require reconstructing the generator.

The supply and demand generation section of AMNET uses the Asset and Work files provided by AMCCOM to construct inputs for MNET. AMNET sequentially constructs and stores a separate node-length array, MSUP(.), for each product, which has a positive entry at each supply node, a negative value at each demand node, and zeroes for all others. AMNET reads in each of the assets for a commodity, adds the amount at the appropriate node, and converts each total to an integer number of short tons. Thus, all demands occuring within a single time period are aggregated for each location. Demands read from the Work file are processed in a similar fashion except that entries in MSUP(.) are negative.

Since the transhipment algorithm, GNET, requires that each commodity exhibit supply equal to demand, provisions are included in AMNET to account for the fact that assets very seldom equal requirements in ammunition distribution problems. A single extra node is added to the network which acts as a gathering point for any excess supply after all demands have been satisfied and a source point for meeting any demands in excess of supply. The demand generator totals the amount of supply and demand for each product and assigns the difference as a single supply or demand at the extra node. If the difference is negative, then supply exceeds demand and the extra node acts as a supersink for the excess supply; if the difference is positive, the extra node acts as a supersource for the demands that cannot be satisfied. Extra supply is absorbed at no cost via arcs connecting each depot in the last time period to the extra node. A large cost is charged for filling demands from the supersource so that demands are not filled with this artificial supply any more than necessary.

The extra node also serves as a distribution system by-pass mechanism for demands which cannot be satisfied within the limits of the specified distribution window. In that case, balance within the network is maintained by diverting enough supply around the body of the network through the extra node to satisfy the problem demand. This prevents high-volume problems from becoming infeasible.

The report writer represents the first step required in post-processing the output of the solution algorithm into useful management information. By reading the output of MNET and iterating through the arcs for each commodity, multicommodity and single commodity results are extracted. Arc numbers are converted back to location names and time periods. Total flow on each capacitated arc is calculated by summing across all commodities, and remaining capacity at each location by time period is calculated and included in the report. The penalty costs associated with backlogging are also summed so that actual costs of shipment can be extracted from the objective function value. Finally, the locations of remaining inventories and the demands filled by artificial flow from the supersource are listed.

Although the prototype programs discussed above are quite simple and somewhat specific to the sample data provided by AMCCOM, they demonstrate the techniques that must be applied in a more general fashion to operate a production version of this system.

IV. SOLUTION METHOD

The MNET algorithm [Ref. 10] used to solve the multicommodity capacitated transhipment problems considered in this thesis is a resource-directive procedure, related to the earlier work of Kennington and Shalaby [Ref. 11] and Held, Wolfe and Crowder [Ref. 12].

The following discussion refers back to the MCTP formulation presented in Chapter III.

The most important observation about the MCTP formulation is that if the constraints on shared capacity (3.3) were deleted, then the problem would decompose simply into a set of independent capacitated transhipment problems (CTP), one for each commodity. This observation is at the core of most solution techniques for MCTP. It also illustrates how the MCTP is a highly structured linear program, although not as neatly structured as the CTP. The MCTP does not have the total unimodularity property enjoyed by the CTP. Because of this property, if a CTP is feasible and has integer-valued b_i then an optimal solution can be found with integer values. This result has important consequences in the design of fast CTP solvers (which have no floating-point calculations), as well as in terms of providing realistic answers in application settings where fractional flows are physically impossible. Unfortunately, as noted, the MCTP does not possess this nice feature. For this reason (and others) the MNET algorithm is heuristic; it searches only among the integer-valued flows and therefore may not achieve the MCTP optimum.

The Kennington-Shalaby/Held-Wolfe-Crowder (KSHWC) approach as well as MNET are based on the companion ideas of <u>resource direction</u> and <u>restriction</u>. The resource direction idea is to allot to commodity k an amount y_{jk} of the capacity of arc j, and then solve for optimal flows within the allotments. It is expressed mathematically as:

choose an allotment $y = (y_{jk})$ where

$$\sum_{k \in K} y_{jk} = u_j, \ \forall j \in A \tag{4.1}$$

$$y_{jk} \geq 0, \ \forall (j,k) \in (A,K) \tag{4.2}$$

and then solve by minimizing (3.1) subject to (3.2) and

$$0 \leq x_{jk} \leq y_{jk}, \ \forall (j,k,) \in (A,K). \tag{4.3}$$

This last problem is denoted RS(y) because the choice of the allotments y affects the definition of the problem. An optimal solution to RS(y) is necessarily feasible but possibly suboptimal in MCTP, therefore RS(y) is referred to as a restriction. The advantage of the restriction is that it decomposes by commodity and can thus be solved by multiple independent calls to a CTP solver. The price paid in return for this advantage is the added burden of having to find appropriate values for the new variables y_{jk}.

The KSHWC procedure has the following form. (The notation v[P] means the optimal objective function value for problem P; LB denotes a lower bound on v[MCTP] and UB denotes an upper bound on v[MCTP]).

Step 0. <u>Initialization</u>: Solve the problem defined by (3.1), (3.2), (3.4) and the constraints: $x_{jk} \leq u_j$, $\forall(j,k)\varepsilon(A,K)$. Set LB equal to the optimal value of this (relaxed) problem. Set UB = ∞ and $\ell = 0$. Choose a relative convergence tolerance $\varepsilon>0$ and an iteration limit L.

Step 1. <u>Allocation</u>: Find an allotment y satisfying (4.1) and (4.2).

Step 2. <u>Restriction</u>: Solve RS(y) and set UB = min(UB, v[RS(y)]).

Step 3. <u>Termination Tests</u>: If (UB-LB)/UB<ε or ℓ = L, stop. Otherwise set $\ell = \ell+1$ and go to Step 1.

The technique employed for Step 1 is subgradient optimization which amounts in this case to revising allotments according to

$$y_{jk} \longleftarrow y_{jk} + \alpha \max (0, c_{jk} - w_{t_j k} = w_{h_j k}) \qquad (4.4)$$

and then mapping the resulting y to the nearest point which satisfies (4.1) and (4.2). Here α is a positive scalar "step size" and $w_{t_j k}$, $w_{h_j k}$ are the optimal dual variables associated with the tail node and head node respectively of arc j for commodity k in the most recent restriction RS(y).

The KSHWC procedure is clearly a heuristic because it may terminate solely on the basis of $\ell = L$. Another disturbing feature of the procedure is that even if the optimal flows in the restriction RS(y) are optimal in MCTP, the convergence test might fail. This is because the lower bound is initially very loose and is never subsequently improved. In spite of these shortcomings, practical experience with the KSHWC procedure has earned it a reputation as a method of choice for dealing with large MCTPs.

MNET employs the following result which helps alleviate the shortcomings of the procedure, increasing both its speed and its solution quality assurance. The result is an optimality test which can be easily administered to the solution of any restriction to see if it is in fact optimal in MCTP.

<u>Theorem</u> [Rosenthal]. Assume x is an optimal solution to RS(y) and let w be an associated optimal dual solution to RS(y).

Let

$$\rho_{jk} = w_{t_j k} - w_{h_j k} - c_{jk} \qquad (4.5)$$

and

$$\pi_j = \begin{cases} 0 \text{ if } \sum_{k \varepsilon K} x_{jk} < u_j \\ \max_{k \varepsilon K} \rho_{jk}, \text{ otherwise} \end{cases} \qquad (4.6)$$

Then x is optimal in MCTP if there does not exist a $(j,k)\epsilon(A,K)$ such that $x_{jk} = y_{jk}$ and $\rho_{jk} \neq \pi_j$.

This theorem has several valuable algorithmic consequences:

1. After a restriction is solved, it can be tested for optimality. MNET has efficient data structures for doing this.

2. One way the optimality condition of the theorem can fail to hold is if for some k,p:

$$\rho_{kp} > 0 \text{ and } \Sigma_k x_{jk} < u_j . \qquad (4.7)$$

This situation indicates that one arc j's capacity is not fully utilized even though commodity p can potentially lower its distribution cost by getting a bigger allotment. Rather than use subgradient optimization in this situation, MNET simply reallocates the slack capacity on arc j to product p when this occurs. This process is called <u>simple reallocation</u>.

3. It can be shown very easily that reallocation by subgradient optimization has a null effect on the capacity allotments for any arc which satisfies the optimality test. Experience with the AMCCOM problems indicates that only a small subset of the arcs fail the optimality test at any one time. Therefore, a great deal of time is saved in MNET, as compared with KSHWC, by ignoring the capacity

reallocation step for all arcs which satisfy the optimality condition.

4. The variable π_j in the theorem is, in fact, a dual variable on the joint capacity constraint of arc j. Equation (4.6) shows how it can be evaluated even though the restriction RS(y) ignores the joint capacities as explicit constraints. We can use this information to improve the lower bound on MCTP. Specifically, we solve a Lagrangean problem,

$$\min \sum_{k \varepsilon K} \sum_{j \varepsilon A} c_{jk} x_{jk} + \sum_{j \varepsilon A} \pi_j \left(\sum_{k \varepsilon K} x_{jk} - u_j \right)$$

subject to (3.2), (3.4) and $x_{jk} \leq u_j$, for all j,k. We denote this problem LR(π). It is a relaxation of MCTP which for any $\pi \geq 0$ is guaranteed to produce a lower bound on MCTP. Note that the KSHWC lower bound corresponds to v[LR(0)]. Solving LR(π) in the AMCCOM problems did not monotonically yield tighter lower bounds, but in most cases, at least one instance of LR(π) had a higher value than LR(0).

The MNET algorithm is summarized in the following sequence of steps which employ the preceding ideas. The notation x[P] refers to an optimal set of flows in problem P.

Table 4-1

MNET Algorithm (Rosenthal, [Ref. 10])

Step 0. Initialization:

a) Solve LR(0). Set LB = v[LR(0)], x = x[LR(0)].

b) Set y = nearest point to x satisfying (4.1)-(4.2). Solve RS(y). Set UB = v[RS(y)], x = x[RS(y)]. Save x as an incumbent solution.

Step 1. Simple Reallocation:

a) If (4.7) holds for any k,p, revise y by simple reallocation and solve RS(y). Repeat this step until (4.7) no longer holds for any k,p.

b) Set x = x[RS(y)], UB1 = v[RS(y)]. If UB1 < UB, replace incumbent solution with x. Set UB = min(UB,UB1).

Step 2. Optimality Test: Compute π by (4.6). If the optimality condition holds, stop.

Step 3. Revise Lower Bound: Solve LR(π). Set LB = max(LB,v[LR(π)]). If (UB - LB)/UB < ε, stop.

Step 4. Subgradient Reallocation and Restriction: If arc j fails the optimality test revise y_{jk} by (4.4). Solve RS(y). Set x = x[RS(y)], UB1 = v[RS(y)]. If UB1 < UB, replace the incumbent with x. Set UB = min (UB,UB1). Go to step 1.

V. COMPUTATIONAL EXPERIENCE

The ammunition distribution model has been tested using supply and demand data provided by AMCCOM. The data is identical to data used in an analysis performed by AMCCOM using ADS. There are 120 items included in the data set with demand for items over the entire horizon ranging from .01 to 22,947 short tons (stons). In 49 cases, supply is less than demand and in 11 cases is zero or near-zero. Also, in about 30 instances, total demands for items are less than 10 stons for the entire time horizon. Because the lowest demand items are not significant in comparison to the largest demands, some of these items have been dropped from large scale analyses; in other instances, the quantities demanded have been increased to make the problem more difficult.

A. BEHAVIOR TESTING

AMNET, the network generator, has functioned as designed during testing. AMNET uses less than .15 CPU seconds on an IBM 3033 under VM/CMS to generate the underlying network of 3,221 nodes and 10,400 arcs, including reading of all input data. About 0.7 additional CPU seconds are required to generate the supply and demand array for each product, including input/output time in the in-core/out-of-core version of the generator. During testing, AMNET successfully balanced products with unbalanced supply and demand, including products with either supply or demand equal to zero, so infeasible problems are not generated.

Initial tests were conducted with single and multiple commodities to insure that the backlogging cost structure elicited the proper responses from the model. The desired behavior is summarized as;

1. Fill earliest demands first;
2. Deliveries should arrive on time if possible, then up to three time periods early, then up to three time periods late (using a three-day time period). If this "delivery window" cannot be met, do not ship;
3. Favor shipment by sea over air whenever possible.

Tests were conducted on both the simple and time-limited backlogging configurations to determine both response of the model and solution times. In both configurations, choice of air versus sea mode is induced by setting the backlogging costs based on transportation costs as follows:

Cost of road/air delivery	\$58 x 1 + \$3500 =	\$3558/ston
Cost of rail/sea delivery (minimum)	\$12 x 2 + 319 =	343
Maximum Cost Differential:		\$3215

During testing, the model consistently selected an on-time air shipment over a 1-period late sea shipment when the backlogging cost was set at \$3250 per ston per time period. When it was set lower, down to \$2850, the results depended on the origin of the shipment. For costs below \$2850, a new behavior appears in which the model consistently chooses to ship on time by air only if a sea shipment can not be made which arrived one period late. Although a complete study of these indications has not been conducted, it appears other "shipping policies" can be induced in the model by properly setting the backlogging cost.

The cost of early arrives, or forelogging, also depends on transportation cost differentials, but response of the model is more difficult to observe because forelogging is only a least cost option in heavily-utilized networks in which the best route to meet a demand is saturated. In the simple backlogging model, the appropriate cost per period to forelog is equal to the cost per period to backlog divided by the maximum allowable periods of forelog minus a small cost to ensure the model selects a maximum forelog before a one-period backlog. In this instance of the model, the desired result is obtained as long as the backlog cost is between three and four times the cost per period of forelogging.

Limiting the backlogging to three time periods is done explicitly in the time-limited configuration, but in the simple backlogging configuration, backlogging must be controlled by the costs on the arcs running from the extra node to the demand nodes. Properly set, these costs induce the model to bypass the network to fill the demand if more than three backlog periods are required, emulating the "do not ship" behavior. However, in order to induce the "fill earliest demands first" behavior, the bypass costs must be monotone decreasing over time. In testing the simple backlogging configuration, these were found to be competing requirements. When a very large cost based on backlogging costs with small increments per time was used, the model correctly limited itself to a maximum of three backlogging periods, but did not necessarily fill earliest demands first. When the cost increment was increased sufficiently to induce the model to fill earliest demands first for short-supply items, maximum backlogging was not correctly limited. In fact, artifical supply from the extra node frequently entered the GLOC echelon and used backlogging arcs to meet demands because backlogging costs were less.

In the time-limited backlogging model, there is no physical connection between time periods in the GLOC echelon, and therefore no problem behavior was encountered. By setting a large monotone decreasing cost on the arcs from the extra node to the GLOC echelon, both "fill earliest demands first" and time-limited backlogging are correctly represented in the model.

Timed tests were also conducted between the two backlogging configurations and between two methods of drawing off the excess supply to determine whether any significant differences in solution time exist. The two methods of drawing off the excess supply were

1. Route it to the extra node acting as a "supersink" from the node where it originates in the network (referred to as TPO for convenience).

2. Draw it through the inventory arcs of the network and route it to the extra node from the last time period (called TP20).

A variety of products was selected to cover high and low supply and demand, excess supply, and excess demand situations. Results are presented in the following table.

Table 5-1

Single-Commodity Solution Times (using GNET [Ref. 1])

Product	Simple, TPO		Simple, TP20		Time-Limited, TP20	
	Time	Pivots	Time	Pivots	Time	Pivots
69	2.167	2410	1.817	2296	1.298	2368
35	2.766	2438	2.466	2561	2.270	2642
7	2.253	2485	2.772	2852	3.095	3170
80	1.218	1984	1.414	2291	1.112	1955
79	1.225	1988	1.128	2151	1.125	1890
115	1.251	1972	1.165	2107	.945	1493
58	2.196	2365	1.967	2298	1.295	2020
68	1.374	2106	2.09	2574	1.208	2158
110	.699	942	.978	1638	.972	1456
102	2.379	2601	2.01	2418	1.155	2029
Totals	17.528	21291	17.807	23186	14.475	21181

The results indicate that, even though there are nearly 1500 more arcs and 260 more nodes in the network, the time-limited configuration requires less time and pivots to solve overall. There is no significant time advantage for either method of handling excess supply, but drawing the excess off at TP20 has the modelling advantage of representing a "close-out inventory" for the system. Consequently, because the time-limited backlog configuration with inventory drawn off at TP20 also displayed a more controllable behavior, it is the preferred version of the model for further implementation.

B. MULTICOMMODITY RESULTS

Analysis of output results indicate that the model applies its shipping priorities in a reasonable fashion for the multicommodity problem. For this particular instance of the problem, the anticipated solution is to ship by air to meet demands occurring earlier than time period 10, with back-logging required for demands occurring earlier than time period 4. Decisions for routing around congested links vary according to the alternatives available, on a least-cost basis. Although the decisions made by the model may be complex for a heavily-utilized transportation network, the interactions observed during testing were rational, usually consisting of selection of another source of supply, a change of mode, or a short backlog or forelog to meet a given demand.

The model seems to choose to fill each demand from a single source by a single route whenever feasible. However, when there is competition for capacity on an arc, the resource directive procedure sometimes allocates capacities in a fashion which forces flows for some commodities to split to other arcs. Similar split deliveries also occur when the best source has inadequate supply to meet a particular demand. Such behavior is contrary to operations in the physical system because it results in additional administrative burden. However, these results can frequently be treated by post-processing to provide a solution which is infeasible in the model, but more acceptable to the physical system.

The model does not provide discrete shipments. Consequently, there are occasionally "optimal" flows which are not desirable in the physical system, primarily from seaports. Although most flows for large problems reach levels which closely approximate shiploads, flows through some ports occur at relatively low levels. In addition, it is possible for flows to depart a port for more destinations than ship loading rates in the physical system actually allow. This problem can be eliminated by expressing the POE to POD arcs as discrete decisions capacitated to represent shiploads, but that is an additional difficulty not included in this formulation. Until that problem is addressed, post-processing of solutions may eliminate some of these problems by redirecting items to another mode or to the same mode in another time period.

C. SOLUTION-TIME EXPERIMENTS

Initial computational testing of the model using MNET was conducted on nine-commodity problems, having over 30,000 rows, 93,000 columns, and 1000 linking constraints. Once proper functioning had been verified, large-scale computational tests were conducted on the IBM 3033 under VM/MVS batch using an in-core/out-of-core version of MNET. Statistics including the number of capacity violations after LR(0), the initial and final percent gap between upper and lower bounds, the number of subproblems solved, and total run time including input/output in seconds are reported in Table 5-2. The value of the stopping parameter, epsilon, is also shown.

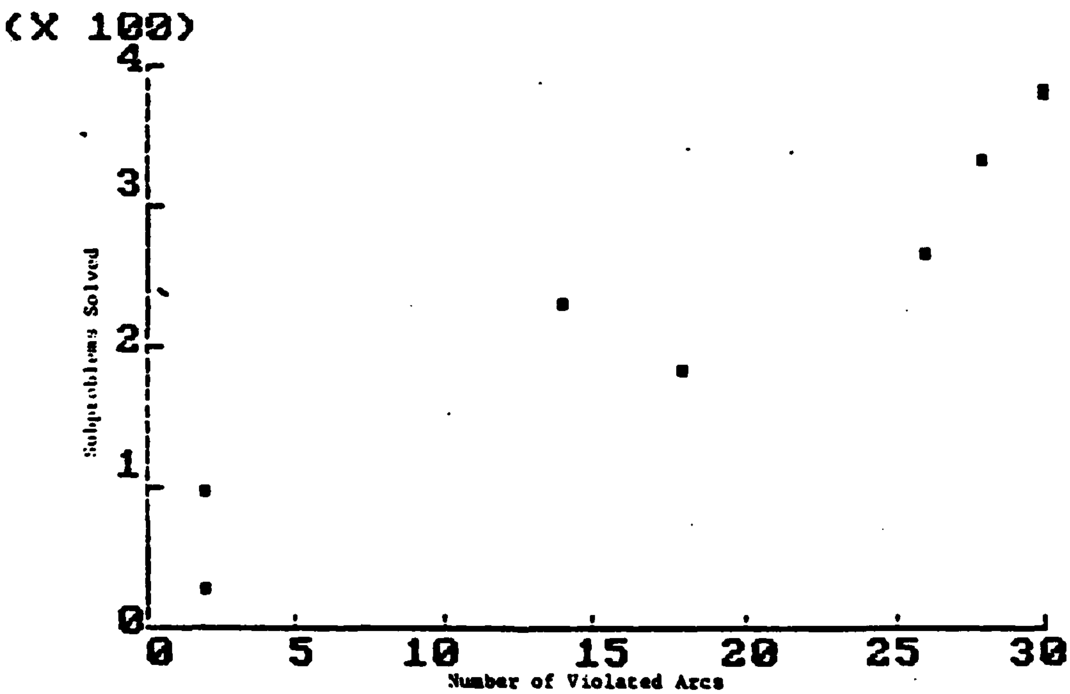
Because the problems were run under varying computer loads, the times are only reported as an indication of turn-around times for each run. Performance of the algorithm is better measured by the number of subproblems solved in solving the MCTP since that provides a more consistent measure of the effort expended on any given test problem. The statistic which seems to be the best measure of the difficulty of a particular problem is the number of

Table 5-2

Multicommodity Computational Results

Products	Epsilon %	Init. Violations	(UB-LB)/UB Gap Initial	(UB-LB)/UB Gap Final	Subproblems Solved	Total Time (Sec.)
9	0.15	2	.145	.066	27	28.8
20S	15.	18	18.4	13.88	184	490.7
40	15.	2	.0101	0.0	98	172.1
40S	15.	26	20.47	13.42	267	698.2
60	15.	14	2.01	1.92	231	254.5
80	15.	28	10.5	10.3	333	420.
100	15.	30	12.9	12.14	382	472.9
100	12.	30	12.3	11.23	379	>960 T

(Notes: S = selected commodities T= Problem terminated due to run time) joint capacities violated at the conclusion of LR(0). The scatterplot in Figure 5 shows that the number of subproblem solutions versus number of violated arcs is roughly linear over the range tested, apparently with little sensitivity to the size of the violations in the arcs. The number of products included in the problem also affects the number of subproblems solved, but its effect is less pronounced.



NUMBER OF SUBPROBLEM SOLUTIONS VERSUS NUMBER OF VIOLATED ARCS

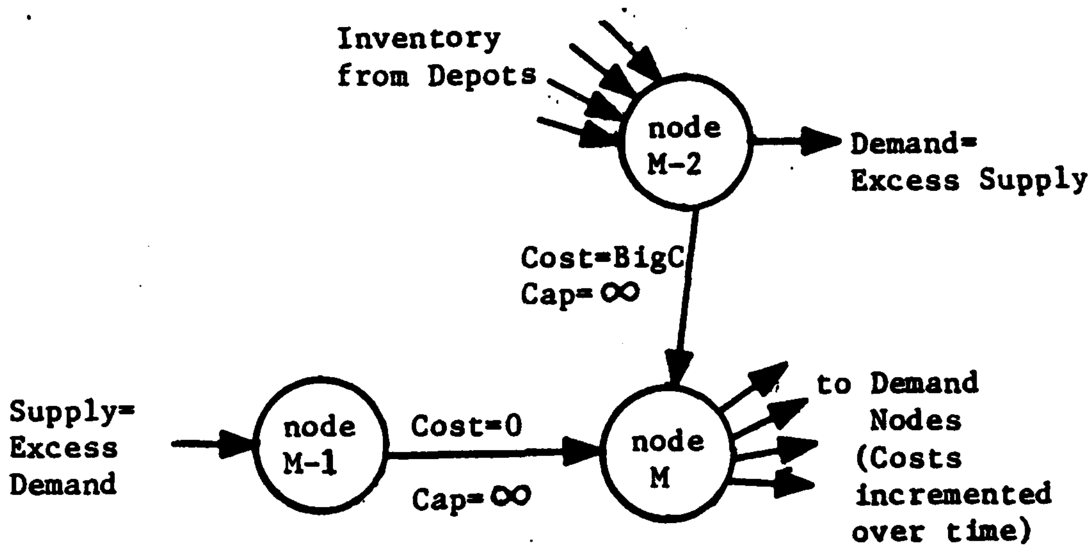
Figure 5.

The results in Table 5-2 were obtained using "comfortable" values of epsilon for the initial large-scale tests. Although several of the test cases started with gaps smaller than epsilon, the results from two runs of 20 and

40 commodities selected for their high demand rate demonstrate the proper functioning of the algorithm when the initial gap is greater than epsilon. For the 20-commodity problem, the gap was reduced about 2% by solving RS(Y) and it was reduced an additional 2.4% by solving LR(π). For the 40 commodity problem, about 3.5% was eliminated in solving RS(Y) and about 3.5% was eliminated in LR(π). These results are encouraging for problems of about medium difficulty among those tested. However, for a 100 commodity problem with epsilon = 10%, the algorithm terminated at the maximum number of subproblem solutions allowed without moving the lower bound. Why the bound failed to move in the harder problem is not known at this time, but is an issue which must be resolved if the final gaps are to be reduced significantly in hard problems.

A large proportion of the time used by MNET is devoted to solving subproblems. In these initial tests, the subproblems were solved from a cold start. Recent tests have shown some improvement in the overall solution time by hot starting each subproblem with a list of candidates obtained from the last solution for that commodity. However, for some hard problems, subproblem solution times increased significantly, probably due to radical changes in solutions between iterations. Work will continue to improve hot start efficiency. For a discussion on hot start technique, see Bradley, Brown, and Graves [Ref. 1].

A large fraction of the objective function values observed in testing is attributed to the penalties on arcs which fill demands artificially (i.e. when demand exceeds supply or when the delivery window cannot be met). For problems in which demand is much greater than supply for one or more products, the associated penalty costs grow rapidly. Rather than arbitrarily reduce the demand to a level closer to available supply, an attempt was made to reduce the cost of artificial supply by restructuring the network bypass system. In the restructured system, three extra nodes, rather than one, are added to the network as shown in the following figure. A large cost is placed on the arc joining the inventory gathering node to the bypass node, and the arcs from the bypass to the GLOC's carry a smaller, incremented penalty. Artificial supply flows from node M-1 to node M at no cost, which amounts to a saving of BIGC units per ton of artificial supply. The results in Table 5-3 compare solutions for one-node bypass and three-node bypass versions of three test problems containing several short-supply items. In each case, the final upper bound for the three-node bypass model is about six-tenths of the final upper bound of the one-node model. However, the actual difference between the upper and lower bounds for each one-node bypass solution differs from the corresponding three-node solution by less than one percent. Such small differences do not seem to be significant. Therefore, although the three-node bypass model has the desirable effect of reducing the overall size of the objective function, it apparently does not improve the quality of the final solution.



3-NODE NETWORK BALANCE AND BYPASS SYSTEM

FIGURE 6.

Table 5-3

Alternate Bypass System Comparisons

Products	Bypass Nodes	Gap Init	Gap Final	Bounds Lower	Bounds Upper	Δ (UB-LB)	% Diff in Δ's
60	1	1.8	1.45	2,863,683,100	2,905,939,700	42,258,800	
	3	3.06	2.5	1,663,492,600	1,706,098,900	42,606,300	.8
80	1	7.25	5.78	3,145,991,600	3,338,980,400	192,988,800	
	3	11.77	9.54	1,813,082,600	2,004,307,400	191,224,800	.9
100	1	9.12	6.37	3,336,141,100	3,563,311,600	227,170,500	
	3	14.83	10.68	1,914,726,100	2,143,572,200	228,846,100	.7

VI. CONCLUSIONS

The computational results demonstrate that the prototype ammunition distribution model functions satisfactorily according to its basic design. However, since a model such as this is potentially useful in support of mobilization planning and exercises, the ability to solve the problem at hand in a reasonable amount of time is as important as the formulation of the model. Again, the results are very encouraging. For the prototype model the common network contains over 3200 nodes and 10,400 arcs, of which about 10 percent have joint capacities. For the 100 commodity test problem, that yields a 330,000 constraint, 1,000,000 variable problem being solved to within about 12% of optimality in approximately 8 minutes. Better performance in moving the lower bound for the hard problems would bring the solution even closer to optimality.

The results provided by this model are valuable for planning shipments and, because of the rapid turn-around times, could be used to assist in actual shipment scheduling. One possible method is an iterative optimization/simulation approach, similar to the method described by Nolan and Sovereign [Ref. 13]. In the AMCCOM situation, the solutions provided by MNET yield not only a feasible incumbent solution upon which to base an initial shipment schedule for the ADS simulation, but also provide a lower bound on the value of the problem from the relaxation and an upper bound from the restriction. It is a simple task to convert these bounds into actual shipping costs, back-logging costs, and costs for failure to meet demands. Backlogging and non-delivery costs may further be converted to stons, providing boundary values against which the output of the simulation may be measured. The possible advantage of this interface is that the simulation may be able to terminate sooner, with an answer of a known quality, providing ammunition managers with more detailed information about their system.

Some issues do remain to be resolved in the modelling effort. The high variability in demands among items and the maximum number of items in a "full scale" problem (AMCCOM supports about 700 items, total) suggest that the products should be classified into perhaps three groups (high, medium, and low tonnage items), and a technique of capacity set-aside used to solve the problems in three classes. Several concerns are overcome by this technique:

1. Each separate class problem may be kept to a reasonable size;

2. Each problem may be solved using a different unit of measure, so that rounding and truncation errors will be minimized in converting from weight to pallets or unit packs, and;

3. Each item will compete for additional transportation capacity only against products in its weight class.

One characteristic of this planning model which is undesirable is the spread of flows to many destinations, in particular upon leaving seaports of embarkation, since this behavior violates physical seaport departure rates and less-than-shipload departure rules in the physical system. Nevertheless, much of this shortcoming may be overcome in translating the planning result to a shipping schedule. To resolve this issue in the optimization model requires discrete modeling of the POE to POD arcs, with lower and upper bounds on each arc. The author intends to pursue research on this particular issue in the future.

Two other areas for future work on the model are the inclusion of multiple measures of capacitation and inclusion of a method of suitable substitution for short-supply items. Implementation of multiple capacitation measures requires modification of the MNET algorithm because the reallocation procedure must be performed on each capacitated arc for each measure of capacity. The throughput representation in Figure 3 may still be used in the subproblems by converting each capacity to short ton equivalents for each product and assigning the most restrictive value to the arc. There will be more computational effort in the reallocation step, but the subproblems, which constitute most of the solution time, will be unchanged. The second issue may prove to be a difficult one due to the heirarchical structure for substitutions observed in the physical system, but is important because the use of substitutes may dramatically influence the optimal solution to a problem.

One major development issue remains in the MNET algorithm. In order to function effectively on extremely difficult problems, a more robust method of improving the lower bound must be found. Work is continuing in that area.

The results obtained on this instance of the AMCCOM distribution problem using MNET are particularly encouraging. Solutions of known quality have been obtained with solution times so short that it is a viable tool even in real-time decision-making and evaluation situations, such as mobilization exercises. Moreover, the solution technology applied to this problem is widely applicable to many other similar distribution problems. With continuing work, both the particular model studied here and the MNET solution algorithm are expected to provide even better results in the near future.

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