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SIMULATION vs. OPTIMIZATION IN PHYSICAL DISTRIBUTION PLANNING

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ABSTRACT

The design of a physical distribution system requires decisions on the number, sizes and locations of warehouses. For each warehouse, one must also address the related issues of which products should be stocked there and which customers it should serve. This paper reviews and critiques the two major approaches for physical distribution planning, namely simulation models and optimization models. These are discussed in light of the various management activities in physical distribution planning and operations. Strengths and weaknesses of the two model types are summarized, and ways suggested in which they may be usefully employed together.

I INTRODUCTION

This paper has 6 major sections following this brief introduction. Sections II and III respectively treat simulation models in physical distribution (PD) and optimization models in PD. Significant PD applications of each model type will be summarized.

Section IV discusses the physical distribution function. What are the major management activities here (transportation, warehousing, inventory control, ...) and how might the various strategic and operational decisions in PD be assisted by a simulation model? By an optimization model?

In Section V, we treat the issues of data required by the optimization or simulation models, and the information needed by PD managers to successfully carry out the activities discussed in Section IV. The degree of overlap or commonality of the various information requirements will be of particular interest.

Section VI deals with "hybrid" simulation/optimization models, or more generally, with combined simulation/analytic models. Such approaches have been successfully employed in PD as well as other operations research (OR) studies. Section VII presents our conclusions.

II SIMULATION MODELS IN PHYSICAL DISTRIBUTION

The technique of simulation permits detailed tracking of the material flows in a logistics system. Before designing and coding a model of the distribution of goods from factories to warehouses to retailers, however, a number of management policies must be specified. Some of these policies will involve highly strategic issues: which products should be stocked at every warehouse and which should be carried only at certain warehouses; should the flow of goods be governed by a "pull" system (when a warehouse determines that it requires more of a product, it places an order with the factory) or by a "push" system (a decision to re-stock is made by the factory, which then pushes the product out to the warehouse), or perhaps by a mixture of the two systems, etc.

These management policies will also involve some operational issues such as the following. Suppose warehouse 1 (W_1) currently has on hand 50 cases of product A while retailer R_4 requires 60 cases. Should W_1 hold up ("backlog") the entire order until it receives an additional replenishment? If so, should W_1 request that this shipment be expedited from the factory, or perhaps even from outside the normal channels, say from another warehouse W_2? Alternatively, the 50 units could be shipped now. If so, should an additional 10 units be shipped when available, or should this remainder be included in the "next" order from R_4? (Perhaps this order will be transmitted to W_1 one period earlier than if the full 60 units had been available.)

There are also related issues which straddle the strategic and operational. One such example is whether the preceding decision pertains to only certain products A, C, F, ... or to all products stocked at W_1. In short, there is a large number of management policies which must be specified. (For some insight into how detailed the specification must be, see [4] where this is accomplished via a "questionnaire".) It is the purpose of this paper to understand the performance of simulation models for physical distribution relative to their optimization counterparts, and to that end, we next review several "famous" PD simulation models.

The Heinz Simulation. A physical distribution simulation of historical significance is that of the H.J. Heinz Co. [22]. This dealt (at the time) with 9 plants, 3 mixing points (regional distribution centers) and 43 warehouses, incorporating 50 different product-consumption patterns for customers. The original model was essentially "static" in nature, allowing no feedback later in the simulated year of the earlier stages' results. Model validation was carried out by replicating the firm's current distribution costs to within several per cent. The model studied in detail 10 alternative distribution configurations in addition to the present one. The final recommendations were to leave unchanged the 9 factories and 3 mixing points, while reducing the 43 warehouses to 32, some of which had new locations.

This use of simulation in PD was noteworthy for several reasons, not the least of which was the model's implementation on the equivalent of today's microcomputer. The Heinz simulation by Shycon was the first of many distribution studies performed by him and his firm. The methodology which evolved was incorporated in a model termed LOGISTEK. As described by Vollmann ([25], pp.395-397), the model now has some "adaptive" features which permit approximate optimization. A set of perhaps 100 candidate warehouses can be narrowed down to 30 or so in about 35 or 40 computer runs, most of which involve a detailed study of location patterns and the tradeoff of cost and customer service. These resulting warehouses could similarly be assigned back to factories, allowing the user to look at product flows in an adaptive way.

These adaptive features permit the model to drive inefficient locations out of the solution. (In this regard, LOGISTEK is somewhat similar to mathematical programming, which of course outputs the optimal warehouse locations.) Inefficiences are noted after each "iteration" by allocating the fixed costs of serving customers from each warehouse. Suppose the total volume handled at a particular warehouse is small. Its total cost per unit shipped will likely be high, even if that warehouse is very close to some customers. In this way, certain warehouses will ultimately be closed while others will now have a higher throughput, thereby lowering the latter's total cost/unit.

In summary, while the original Heinz simulation assigned customers to warehouses based on closest distances, the later version of the model treated this and other aspects more carefully. At least 15 years after the original Shycon study, Heinz was still employing simulation to assist in physical distribution decisions [6].

Other Simulation Models. Other well-known models for PD simulation are described by Bowersox [3]. These include the static simulator DPM (Distribution Planning Model) and the dynamic simulators DSS (Distribution System Simulator) [4] and LREPS (Long-Range Environmental Planning Simulator). Both DSS and LREPS may, at the option of the user, be run as probabilistic rather than deterministic models. In principle, this stochastic feature is an advantage of simulation over optimization. Nevertheless, the use of a probabilistic model also requires a good statistical analysis of simulation output [14]. Since statements about model results will now be phrased in terms of confidence intervals rather than point estimates, a stochastic PD simulation is viable only when there is a "small" number of random variables. At least in the case of DSS, most of the probabilistic features would therefore not be used for a given run.

In any case, the Heinz model plus the three mentioned in the preceding paragraph are very realistic, successful simulations of multi-echelon physical distribution systems. In Section VII we will critique the use of simulation for distribution system design, after we have discussed the PD function (Section IV) and data requirements (Section V) for PD management and modelling. We turn now in Section III to optimization models in physical distribution.

III OPTIMIZATION MODELS IN PHYSICAL DISTRIBUTION

It is worth mentioning at the start of this section that we are referring to optimization models for the planning of PD. Thus, although optimization techniques have been highly successful in the routing and scheduling of delivery vehicles, or in determining good inventory policies, these applications are excluded from consideration at the moment. (We will return to such operational questions in Section IV on the PD function and in our conclusions, Section VII.)

Rather, we are concerned here with optimization models for the design of a distribution system: How many warehouses should there be, of what size and location, and what are the appropriate product flows? The latter question asks, "what are the optimal assignments of factories to warehouses and of warehouses to retailers," and which products should be stocked at a given warehouse?"

Geoffrion and Graves [9] have formulated and solved this mixed integer programming (MIP) problem with a great deal of success [10-12]. The objective is minimization of total costs, including those of pipeline inventories, transportation, the fixed and variable costs of warehousing, and possible penalty costs if a warehouse is operated at a throughput level outside the desirable range. Example of the constraints include: factory supply limitations for each product group; retailer demand requirements by product; the assignment of each retailer to a single warehouse for each product group; plus a great many configuration constraints involving 0-1 variables.

The size of this problem is very large. For the application at Hunt-Wesson described in [7,9], there were 17 product groups, 14 factories, 45 possible sites for warehouses and 121 retailers. This resulted in a model with approximately 23,000 continuous decision variables, 700 0-1 variables, and 11,000 constraints. Nevertheless, in very moderate computer time, the model is solved to near optimality.

Moreover, with careful use of the modelling flexibility offered by the 0-1 variables, this MIP problem allows the same realistic restrictions on system configuration which are met in practice. (These restrictions can of course be handled in simulation, since one generally pre-specifies the PD systems to be simulated.) Common illustrations are minimum and maximum throughput volumes for each warehouse; limiting at most two of the three warehouses W_1, W_4 and W_6 to be open, etc.

Many more examples of system restrictions, and the ease with which a skillful modeller may take care of them in MIP, are presented in [11].

Whether one employs a simulation model or an optimization model, the initial run or model solution is less important than are answers to "what if" questions (as a simulation practitioner might say) or the results of "related secondary runs" (see [12]). An optimization practitioner would generally call the latter "sensitivity analysis", at least in the case of linear programming, where this is performed with the help of duality. That the work of Geoffrion and Graves [8,11] permits these secondary runs to be carried out with such ease is remarkable: there are no MIP "shadow prices" to assist in this task.

Geoffrion has argued [7,8] that the technique of simulation is inferior to his choice of optimization for distribution system design. Optimization was said to be the only approach which enables one to distinguish between two alternatives whose differences in total costs are small; to easily perform related secondary runs of the model [12]; and to know that because one has the optimal solution, the model's clients may be more readily convinced of the validity of the results.

There is much merit in Geoffrion's comments and of course in his work itself. It should be pointed out, however, that the use of such a large scale optimization model is dependent upon an organization's prior familiarity and expertise in mathematical programming, and may require considerable support from the firm's data processing personnel.

Intelligent use of mathematical programming will generally involve 7 steps (some of which will of course be repeated in feedback fashion):

1. model formulation
2. data preparation and checking
3. data entry
4. initial model runs
5. "secondary" runs
6. interpretation of model results
7. recommendations.

OR personnel are generally quite good at the latter two stages, so 6 and 7 will not be considered further. Item 2 is generally the bottleneck for any large OR study, whether optimization or simulation. If there is a tight deadline for this assignment and yet the data is not available in the proper form (is it ever?), there is not much more to be said. So, let us assume that the deadline is not tight.

Step 4, initial model runs, is not difficult in itself. However, the software to carry out these initial runs must be obtained either through:

a. purchase
b. lease, or
c. time sharing.

Options a. and b. generally require more than that the OR group be familiar with large scale mathematical programming. It is often the data processing department which controls a firm's batch computing resources, allocating time on "their" machines. Without DP support, therefore, purchase or lease of optimization software is not to be recommended. (Indeed, without this cooperation, Step 3 and perhaps also Step 2 will be difficult as well.)

Obtaining the data processing department's support for an optimization application may require more than just a good rapport between the respective managers of OR and DP. Rather, some DP personnel should themselves have prior familiarity with mathematical programming. In this writer's experience, that is not a simple requirement to meet. DP staff get far more reinforcement for skills in software development. If a systems or technical support analyst has worked previously with even ordinary LP, it is more by coincidence than by design. The only choice left for Step 4, then, is c., time sharing. It is expensive, and by its very nature is more conducive to a "one-shot" study than to an on-going effort in PD modelling. As a result, there will still be (apart from the OR group) no familiarity with mathematical programming in the organization, either in the data processing department or among potential management users.

It is especially for such an organization that simulation may be a real alternative to mathematical programming. The capabilities required for use of a simulation model are generally achievable. It is much easier to explain to management what a simulation model does. In addition to the OR group, the DP staff have also had the experience with simulation, as witnessed by the recent widespread use of corporate financial simulation models (see Naylor [18,19]). Thus, assuming availability of the computing resource, a PD simulation is not likely to require outside time sharing and is more likely than optimization to lead to an on-going effort in PD modelling.

I have discussed the remarks of Geoffrion with about a dozen industrial practitioners in Canada, and have yet to hear one say that optimization would be of more use to him than would simulation for distribution system decisions. What is there about the real-world settings in which these OR and distribution practitioners work which make simulation more attractive? To shed some light on this question, Section IV outlines the management functions which must be carried out by an organization's PD staff.

IV THE PHYSICAL DISTRIBUTION FUNCTION

"Physical Distribution" refers to that set of management activities which must be carried out to move finished goods from the final production line to the consumer. PD is thus the direct connection between manufacturing and marketing, and generally includes the management functions of:

A. Inventory Control (finished goods)
B. Customer Order Processing
C. Materials Handling and Packaging
D. Warehousing
E. Transportation (traffic).

There may not be uniform agreement that PD includes precisely the above, and no more and no less. For example, the traffic manager of a vertically integrated firm may be able to arrange that required raw materials be carried as back-hauls in company-owned trucks. If this becomes a regular activity, it would be logical for Purchasing to be considered part of Physical Distribution as well. Nevertheless, the discussion here will suffer no loss of generality by confining attention to the preceding five functions, each of which is assumed led by a person whoe title is "Manager of ____", with these managers all reporting to the same individual, say the "Vice-President - Physical Distribution". (Again, not all would agree that this form of organization and reporting structure would be best.)

The five functions A through E generally involve operational decisions more than strategic ones. However, there are important issues of strategy, often in the area of overlap between two or more of these functions, which is why they should be coordinated by someone at the Vice-Presidential level. Familiar examples of such strategic questions include:

i) Should one or more new warehouses be built, and if so, where? (Tradeoff between the costs of inventory carrying and transportation.)

ii) Should all products be stocked at every warehouse? (Tradeoff between inventory carrying costs and customer service.)

iii) Should air freight ever be used, or should all shipments travel by surface mode? (Tradeoff between customer service and transportation costs.)

Only someone at a level higher than that of Managers of A through E can resolve issues such as these which cut across departmental boundaries; greatly impact the company's competitive posture; and may involve capital investments of considerable size.

Question (i) is of the latter type and is not easy to reverse if answered in the affirmative. (i) is clearly a non-routine decision of the sort that the Vice-President of PD should include as part of an intermediate - or long-term facilities plan. An optimization model would appear to be the appropriate tool if the number of alternatives (feasible warehouse configurations) is at all extensive.

Issues (ii) and (iii) are also strategic. They require the Vice-President for coordination, but in contrast to (i), are not cast in stone once decided. Questions (ii) and (iii) are more typical of ones generally encountered in Physical Distribution. Management needs a model to estimate the detailed consequences of such issues. They are at least partly operational and although not "routine", still similar to those regularly met in PD. Managers of A through E and the Vice-President would greatly benefit from the appropriate "what if" simulation model here.

Naturally, these managers also confront numerous problems within their own purview, ones not cutting across departmental lines. The managers must estimate the implications of these every day decisions. Here again, simulation modelling is generally the appropriate tool to deal with shorter-range issues.

The discussion above focused on the management decisions which are made in physical distribution planning and operations. Another way to approach the question of model type is to study the data or information requirements, both from the point of view of that needed to perform functions A through E, and also the data necessary for use of a simulation or optimization model. These are the subjects of Section V.

V INFORMATION REQUIREMENTS

Ballou [2, Fig.13-6] has summarized the types of information needed for logistics (PD) management. These consist of myriad cost elements, often broken down into their fixed and variable components, of essentially the costs of managing functions A through E. These costs elements are quite detailed, as may be seen by considering a specific example, that of transportation. The main categories here are the costs of private carriage and the costs of common/contract carrier.

There are 5 major types of operating costs associated with running a company-owned trucking fleet: equipment maintenance, terminal operations, insurance, transportation (including fuel, labor and supervision), and "other" costs (e.g., taxes and licenses). The capital costs of private carriage include elements of depreciation and financial charges. Private carriage will not be considered further here, since it may be assumed that a firm has done a one-time strategic study of the risks and benefits of operating a private fleet. Even if it has decided in favor of a private fleet, it will still need occasionally in peak periods to contract work by common carrier truckers.

The latter is just one example of decisions which PD personnel must often make concerning mode of shipment. These decisions may lead to as many as 9 types of common/contract carrier costs in Ballou's category:

- Rail Freight
- Rail Freight CL (car load)
- Truck LTL (less than truckload)
- Truck TL
- Air Freight
- Forwarders
- Shippers Associations
- TOFC (trailer on flat car, or "Piggyback")
- Water Freight.

Obviously, for a given origin and destination, very few of these 9 types need be considered. Nevertheless, virtually every OD pair will have at least 2 mode possibilities. It is by such choices, sometimes routine and automatic but often not, that the firm's Manager of Traffic and Transportation earns his daily bread.

Let us consider now these common/contract carrier cost elements. They may be viewed as having the form $C_{ijk\ell m}$, where the subscript:

- i indexes products
- j indexes origins (factories)
- k indexes warehouses (actual or candidate through which goods are transhipped)
- ℓ indexes destinations (customer or customer groups)
- m indexes mode ($m=1,2,\ldots,9$).

In this case, the data required to manage traffic or transportation are essentially the same as that required by the optimization model.

With the exception of mode m, the notation above is that of Geoffrion, Graves and Lee [11], whose MIP model employs freight rates which are weighted averages reflecting the mix of modes and shipment sizes deemed likely to prevail. How accurate is this approximation? These authors feel it is quite accurate because each customer ℓ receives all its shipments of product i from a single warehouse k. With this 1-1 correspondence between pairs $(k\ell)$ and product i, the annual quantity shipped on that route (if used) can be assumed known, hence so is the annual cost of transportation outbound from the warehouse.

Because of production capacity constraints, such a 1-1 correspondence need not exist between factory-warehouse pairs (jk) and product i, hence there is less knowledge of the inbound transportation cost on a given link (jk) even if it is used. However, this is not the major issue. The key point is rather that the model's transport costs are annual figures. While it is certainly possible that these modal decisions and shipment sizes may average out during the course of a year, this cannot be known without doing at least a small pilot test. One would choose certain $(ijk\ell)$ combinations and, employing representative shipment sizes randomly drawn over the course of the weeks and months, make the modal decisions in "real time" with the then prevailing rates. This of course is one replication of a simulation. Its use may assist in validating the transport cost elements employed in the optimization model. The ramifications, however, extend considerably further than model validation.

Transport cost elements have always depended upon the particular product and mode, as well as the OD pair involved. In recent times, however, deregulated rates have been much more free to fluctuate. The effect of deregulation, plus the probable importance of modal choices, may make it less likely that the MIP model can finalize the recommendations on distribution system design. Rather, the best few warehouse configurations should then be subject to further detailed testing, as in the simulation above. This is an example of a "hybrid" optimization/simulation model, which is the subject of Section VI.

Before going on, however, we remark that the data requirements of a simulation such as the Heinz model [22] and especially the needs of one like the Distribution System Simulator [4] will consist of much more than simply transport cost elements. A simulation follows in detail the flow of goods between echelons, which requires knowing the "disciplines" on the queues of customer orders at each echelon; possibly some details of materials handling; and so on. It would rarely be realistic to attempt a full scale PD simulation with "everything" varying at once. However, to answer detailed questions appropriate to the concerns of one of the Managers A to E, the number of variables and parameters will be quite reasonable. For the Manager of Transportation, decisions concerning modal choice are of this type, and at least here, simulation is competitive with optimization.

VI COMBINED SIMULATION/OPTIMIZATION MODELS

In this section, we consider models that are "hybrids" of simulation and optimization or, more generally, combined simulation/analytic models.

It should be recognized that optimization models in particular, and analytic models in general, need not represent a point of view entirely opposed to simulation. Rather, the two model types can reinforce each other. Ignall et al [13] have employed simulation as an aid in the development and validation of analytic models. Detailed simulations of travel times were found to be quite consistent with simple analytic expressions previously derived by the authors based upon reasonable geometric arguments. This is the simulation analog of Geoffrion's [8] use of an analytically solvable "minimodel" in conjunction with a large scale mathematical programming model. By making certain simplyfying assumptions (e.g., demand/unit area is uniformly distributed, candidate warehouses all have identical cost characteristics), he was able to derive algebraic expressions for such quantities as the optimal number of open warehouses. Such expressions greatly assist in obtaining insights from the numbers output by the larger-scale model.

Traditionally, specialists in simulation or in optimization have argued that these methodologies are intended to address different issues. To some extent, we have so argued in this paper. However, with ingenuity, one can do almost anything with either model type (simulation or optimization) that could be done with the other. Solomon [24] has shown how stochastic simulation may be employed for sensitivity analysis in a product-mix linear program. More precisely, she has emphasized that an optimization model must generally take as constant or deterministic certain parameters which are in fact stochastic. (One example of this is the rate at which raw material or work-in-process arrives at a production station.)

Extension of the latter reasoning would say that generally one cannot optimize, since the data are uncertain. Narasimhan [17] has made this point in studying the problem of site selection for a warehouse or other facility (although in fact he does not argue in favor of simulation either). An experienced practitioner of optimization, however, would have no trouble in treating "uncertainty" via extensive sensitivity analyses and parametric programming [8,12]. This assumes, naturally, that one can isolate the sources of uncertainty and that these are very few in number.

Just as one can essentially "simulate" with an optimization model, one can attempt to "optimize" with a simulation model. Smith [23] and more recently Biles and Swain [1] have studied methodologies for the latter. These approaches determine the best levels for the simulation's controllable variables so that the output "response" is optimized. If this is viewed as the logical or mathematical generalization of the simulation's results, it has somewhat the flavor of Geoffrion's minimodel.

Zeleny [26, Chapter 10] has also pointed out that, rather than optimizing a "given" system, it is much more important to "design an optimal system". For the physical distribution problem, we contend that a pure optimization model is inferior to a hybrid simulation-optimization model to accomplish this optimal design. (See our comments in Section VII. Geoffrion [7] supports this point to some extent as well.) Indeed, Nolan and Sovereign [20] have used recursive optimization and simulation in their analysis of transportation systems. Rosenfield and Norris [21] have discussed "what if" modelling in physical distribution. The latter's approach to scenario evaluation often involves a sequential search in which an optimization is a step within the sequence. They show several ways in which "what if" (i.e., simulation) models may be used in conjunction with optimization models.

It may also be important to consider multiple criteria in the planning and design of a distribution system [15]. To date, such multiple criteria models have generally been of the mathematical programming type [26]. That is, these are of the form:

$$\left\{\begin{matrix} \text{opt } Z_1 \\ \\ \text{opt } Z_2 \end{matrix}\right\}$$

subject to some constraints. In the PD context, we wish to, say, minimize total costs and maximize customer service. Naturally, these cannot be accomplished simultaneously. The results of such a 2-objective model would include the best tradeoff possible between cost and customer service.

Well-designed simulation models [14,18] do of course furnish a number of output measures. There is no reason why several of the endogenous variables obtained from a simulation could not be used as inputs to such a multiple-objective mathematical programming model.

Today (1984) there appears to be less difference than the textbooks would indicate between optimization and simulation. In addition to a model which alternates between these two types [20,21], an optimization model may also be part of an interactive decision support system (see, for example, Dyer and Mulvey [5]). A simulation model (such as a corporate planning model) may contain an imbedded optimization routine for, say, production planning [18]. The interrelationship between simulation models and optimization models for distribution system planning may in fact hold in a wider context.

VII CONCLUSIONS

In this paper, we have attempted to contrast the differences between simulation models and their optimization counterparts in the specific application to physical distribution planning. Their relative strengths and weaknesses have been highlighted in several ways.

Simulation models were found to be more capable of specifying the details of the management policies implied by specific distribution system configurations and customer service levels. It is easier to explain to Management what a simulation model does. Intelligent use of an optimization model requires that the organization have prior experience with mathematical programming. Analogous experience is no less required for intelligent use of a simulation model, but it is much more likely that data processing and management personnel already have such exposure. One example of this is the widespread use of simulation models for corporate financial planning [18,19]. Informal conversations with physical distribution and even OR staff have indicated that a simulation model was perceived to be of greater assistance than an optimization model for PD decisions.

This perception can be understood, however, by studying as we did in Section IV the various management activities in physical distribution. Although many of these cut across departmental lines, the decisions themselves are more operational than strategic. Thus, while a decision to stock a particular product group at only certain warehouses has important consequences for marketing strategy, its implications can be easily tested with a simulation model. If one accepts the hypothesis that most decisions in PD management are of this type (important but not irreversible), then a "what if" simulation model is seen to be of great assistance to physical distribution Management.

Nevertheless, the mixed integer programming model of Geoffrion and Graves ([9,11]; see also [8,12]) would be of great utility for the planning of a new distribution system or a critical evaluation of an existing one. Optimization is a more appropriate tool here, since it can implicitly evaluate all the thousands of warehousing alternatives available when, e.g., we are to consider both the relocation of existing warehouses as well as increases or decreases in the number of open distribution centers. The work of Geoffrion has enjoyed great academic and bottom-line success, and deservedly so. This optimization will output the best configuration of warehouses and the corresponding factory-warehouse and warehouse-customer assignments. Although the modified (adaptive) version [25] of the successful Heinz simulation [22] does drive "inefficient" warehouses out of the solution, this model is still limited to evaluating in detail only those distribution configurations which have been pre-specified.

An increasingly popular way for the modern practitioner to approach PD decisions and operations is "Distribution Resource Planning" [16]. DRP recognizes the dependent nature of the demand between successive levels in a multi-echelon distribution system. (This is analogous to MRP for manufacturing where the demand for a component part is dependent on the demand for the "parent" item containing these components.) The "distribution structure tree" of DRP expresses which factories F_1, F_2, ... serve which warehouses W_1, W_2, W_3, ... and which of these in turn serve the various retailers $R_1,\ldots,R_n$. The detailed operations of a DRP system are quite straightforward to study with a simulation model. The precise design of the distribution structure tree, however, is exactly what is output by Geoffrion's optimization model.

In Section V we reviewed the data and information requirements for optimization or simulation models and for PD management decisions. We specifically considered the decisions on the mode of transportation by which shipments between two given points should be sent. Although Geoffrion's work treated modal choice as an "average" over all modes, we argued that the choice of mode is an important decision in PD, especially in light of recent deregulation in transportation rates. The accuracy of this averaging over transportation mode must therefore be tested by simulation.

The latter is one illustration of how simulation and optimization can be used together and can reinforce each other, as we discussed in Section VI and as Geoffrion [7] has discussed as well. Such combinations of simulation and analytic models may be expected to be more prevalent in the future, and in other contexts beside that of physical distribution.

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