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AN OPTIMUM-SEEKING APPROACH TO THE DESIGN OF AUTOMATED STORAGE/RETRIEVAL SYSTEMS

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ABSTRACT

This paper reports on an optimum-seeking approach to the design of automated storage/retrieval systems. The method was developed to improve the effectiveness with which simulation models of such systems can be used as design aids. The system modeled consists of several aisles of storage bins, storage retrieval devices (stacker cranes), closed loop conveyor, work stations, and input/output buffers to interface with the conveyor. Since simulation models are only descriptive in nature, there is no algorithmic way to proceed toward an optimum design specification. Starting with an expected value or balanced flow model, however, the simulation can be used to develop a cost effective design. An interactive program assists the designer in developing the expected value model. From this point, optimum-seeking rules or heuristics are used in conjunction with the simulation model to reach a local optimum solution. Several rules are proposed and evaluated.

INTRODUCTION

This paper reports use of a simulation model to assist in the development of design heuristics for an automated storage/retrieval/delivery system. These systems consist of several aisles of storage bins, storage retrieval devices (stacker cranes), a closed loop conveyor, work stations, and input/output buffers to interface with the conveyor. Directed by computer, the stacker cranes retrieve storage bins from the racks and place them on the buffers to access the conveyor for delivery to a work station. At the work station, parts might be removed for order picking, replenished, or have some other activity performed. The bins are subsequently placed on the conveyor for return to the storage aisles and replacement by the stacker cranes in their original locations. The control program, is constantly made aware of the status of all components of the system through sensing devices and interace with the computer. Thus, all actions can be directed and monitored by the computer.

These systems are coming into widespread use in both manufacturing and service settings [4,5]. Two common applications are: storage and order picking of small parts, and storage and retrieval of patient hospital records. However, efforts to predict system behavior before the system is actually constructed have been neither extensive nor very complete in formulation [1,2,3,10,11]. This paper describes the use of a simulation model which permits experimentation with alternate system configurations and operating policies to provide insight into designs which can be "fine tuned" through more extensive simulation.

The model was programmed in FORTRAN. A general purpose language was chosen over a simulation language for two reasons: to maximize the ability to transfer the model between computer systems, and to achieve maximum flexibility in adapting to the real world through easily made changes in the program. Subsequently, the model was rewritten in GPSS to take advantage of the isomorphism of language elements with real system components. This conversion provided the opportunity to contrast the programming effort and running efficiency for the two versions. These results have been reported elsewhere [7].

THE PHYSICAL SYSTEM AND ITS OPERATION

The physical system is depicted in Figure 1. It is comprised of specially designed storage racks arranged in aisles which contain the bins, stacker cranes which travel horizontally and vertically to a designated position to store or retrieve a bin, and a closed-loop, powered, roller conveyor (with appropriate crossover and transfer devices) to transport bins between the storage racks and the work stations. At each storage rack aisle and each work station, sections of powered rollers act as input and output buffers for bins coming off or going onto the conveyor. Each aisle has both an input and output buffer section, while each work station has its own input buffer but shares an output buffer with an adjacent work station.

Under computer control, bins are selected and dispatched to specific work stations based on the status of all work stations. Stacker cranes execute either dual commands (storage of one bin and retrieval of another on the same trip), or single commands (either storage or retrieval of a bin), depending on availability of bins and other system status measures. Bins are initially deposited in output buffers at the ends of the aisles, and then put onto the conveyor as space becomes available. Upon reaching a work station, a bin is placed in the input buffer, and ultimately reaches the last buffer position, or work position. The required activity occurs for the bin, and it is then placed on the output buffer for eventual transfer to the conveyor and transport to the storage rack aisles for replacement in the position from which it was taken. If there is no room at a stacker or work station destination, the bin is recycled on the conveyor until it can be accommodated.

Efficient operation of the system hinges on continuous and accurate information on system status. For example: which work stations have room at input buffers to receive a bin, which work station has the shortest supply of bins, what will be the status of a work station when a bin dispatched to it arrives, and how fully utilized is the conveyor.

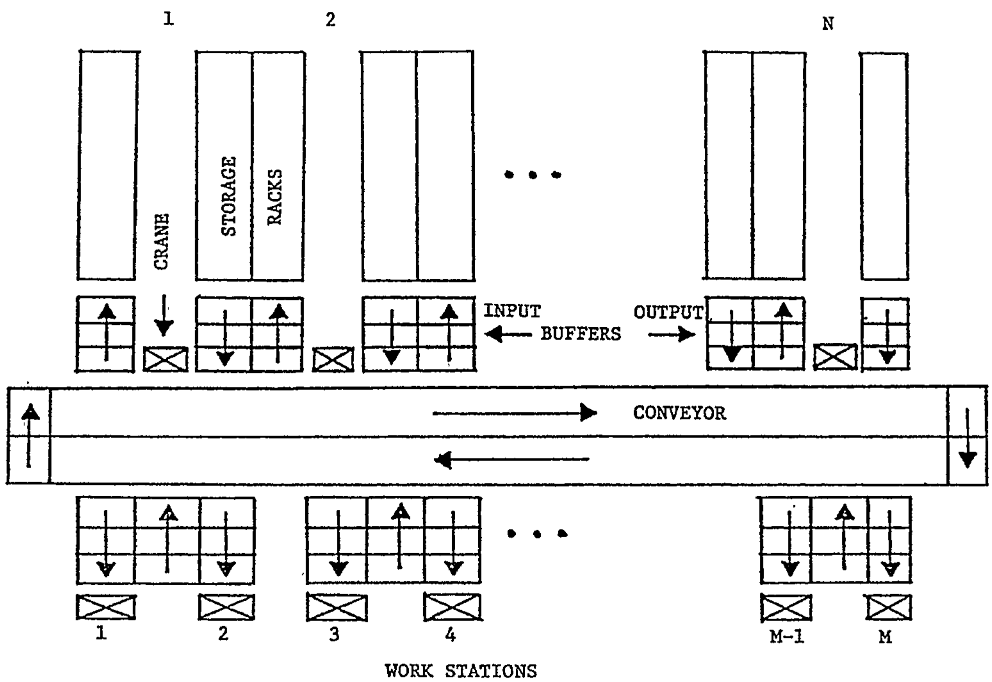

Figure 1. Physical Layout of Storage Retrieval System

PROBLEM FORMULATION

System Variables

Design Variables: The design variables describe the physical configuration of the system and the dynamics which govern the movement of its components. Design variables included in the model are:

- Storage rack dimensions: length of aisles, height of racks, and number of storage locations, segregated by zones
- Number of stacker cranes: one crane per aisle
- Horizontal acceleration and velocity of cranes
- Vertical acceleration and velocity of cranes
- Number of input and output buffer positions at each aisle
- Conveyor geometry: shape of conveyor and location of all system elements around the conveyor
- Length of the conveyor
- Speed of the conveyor
- Number of work stations situated around the conveyor
- Number of input buffer positions at each work station
- Number of output buffer positions shared by each pair of work stations
- Work station dwell times: probability distributions for the service times at all work stations

It should be noted that choices for many of these variables are quite constrained by available equipment options.

Operating Policy Variables: Operating policy variables are used to control the actions of the system for efficient and effective performance. Judiciously setting these values provides smooth flow of bins from storage racks to work stations and back again. Some of the operating policy variables included in the model are:

- Zone storage definition for bin locations in the racks: zones are defined as sets of storage locations which have equal crane travel characteristics
- Maximum conveyor utilization: prevents "log jams" on the conveyor which might preclude bins from returning from work stations
- Maximum number of bins destined for a single work station: prevents exceeding work station buffer capacity and possible recycling of bins
- Maximum number of bins destined for a single aisle: prevents exceeding aisle buffer capacity and possible recycling of bins

Although operating policy variables can have a significant impact on overall system performance, the focus of this paper is on the physical system design.

System Performance Measures

Complex systems such as the one modeled here, have many measures of system performance which could be of assistance in their design. The model provides the following set of measures which were selected in consultation with the system designers/manufacturers.

- Throughput (number of bins per hour delivered to all work stations): a measure of system capacity
- Number of bins recycled: an indication of lack of system component synchronization
- Utilization of stacker cranes by category (dual commands, single commands, and idle time): a measure of crane efficiency
- Conveyor utilization: a measure of conveyor conjestion
- Utilization of work stations by category (busy, idle, and blocked): a measure of work station capacity
- Dollar cost of the system

THE SIMULATION MODEL

The model was initially written in FORTRAN and developed on a VAX 11/780 system. The program consists of a set of functions and subroutines permitting running a given configuration for whatever period of real time the user desires. Alternatively, a heuristic rule may be specified which will run several system configurations until its stopping condition is satisfied. Results can be printed at regular time intervals specified by the user with a summary set of results given at the end of the each run. The model is designed to run the system for an interval of time elected by the user to achieve steady state before accumulation of statistics commences.

The model is an event-oriented discrete time simulation which represents behavior of bins circulating through the system. Bins are retrieved from the storage racks. Location is defined by zones within an aisle and travel times of the stacker are calculated according to the zone centroids. Bins will retain aisle and zone identity throughout the travel on the loop and will be returned to their starting locations.

The major events that are used in the program are as follows.

- Bin Arrival at a Work Station
- Work Station Service Completion
- Work Station Belt Try
- Bin Arrival at Stacker
- Stacker Service Completion at Home
- Stacker Service Completion in Aisle
- Stacker Belt Try
- Zero out Statistics

THE DESIGN PROCESS

An Expected Value Model

Our objective is to provide system designers with guidelines which will aid in the development of systems which achieve desired performance goals at reasonable cost. These systems are complex and difficult to design because of the large number of design variables which may be manipulated. Furthermore, system behavior is stochastic. Bin movement is a random variable due to the probabilistic behavior of both work stations and stackers.

As a starting point for the design of a particular system, we consider a simple expected value model (EVM) which will yield a design balanced in bin flow at the stackers, the work stations, and on the conveyor. This approach is analogous to the determiniaitic models of Kwo [6] for storage/delivery conveyors.

Stacker Flow Capacity:

Let

S = expected value of stacker capacity (bins/hr.)

$t(s)$ = expected value of time to execute a dual cycle (sec./bin)

n = number of stackers

Then $S = 3600n/t(s)$

For example, a system with an expected value of dual cycle time of 30 seconds and 10 stackers wouldhave a delivery capacity at the stackers of:

$$S = (3600 \times 10)/30 = 1200 \text{ bins/hr.}$$

Work Station Flow Capacity:

Let

W = expected value of work station capacity (bins/hr.)

$t(w)$ = expected value of dwell time at work stations (sec./bin)

m = number of work stations

Then $W = 3600m/t(w)$

Thus 20 work stations each with an expected value of dwell time of 60 seconds would have a delivery capacity of:

$$W = (3600 \times 20)/60 = 1200 \text{ bins/hr.}$$

Conveyor Flow Capacity

Let

C = capacity of the conveyor (bins/hr.)

c = conveyor speed (inches/sec.)

l = bin slot length, or bin length plus bin separation (inches/bin)

Then $C = 3600c/l$

A conveyor speed of 24 inches/sec. in a system using 36 inch bins with a separation of 36 inches between them could deliver:

$$C = (3600 \times 24)/72 = 1200 \text{ bins/hr.}$$

The theoretical capacity of this system is then 1200 bins per hour. This assumes completely deterministic behavior of all system components, 100% utilization of the conveyor, and 100% dual cycle commands. None of these assumptions hold for real systems. However, this system is an appropriate initial design from which to begin. The expected value model provides starting values for the design variables: number of stackers, number of work stations, conveyor speed, and minimum conveyor length (the sum of the widths of all stacker aisles and work stations). Using optimum-seeking rules in conjunction with the simulation model, we can then alter various system components to approach the theoretical limit.

It should be emphasized that the capacities above are theoretical upper bounds and cannot be attained by design, due to the stochastic nature of the system. For example, the theoretical belt capacity cannot be achieved since a bin arriving at a stacker will be discharged to to the stacker buffer, and that belt position will remain empty until occupied by a bin at a later time. Similarly, 100% dual commands executed by the stackers is an unattainable goal.

An interactive program was written to assist the designer in developing the expected value or balanced system model. Using successive questions, the program elicits the description of the proposed system from the designer. The necessary input data are: desired throughput or bin flow, assumed fraction of stacker commands which are dual cycle, description of zones and probability of access, stacker travel times, work station dwell times, bin length, bin separation, and width of stacker aisles and work stations. The design variables specified by the program are: number of stackers, number of work stations, conveyor speed, and minimum conveyor length.

The major inputs for the illustrative system described below include:

throughput = 700 bins/hour
dual stacker cycles = 60%
number of zones = 1
dwell time = 30 seconds
bin length = 36 inches
bin separation = 54 inches

The expected value or balanced system model produced by the program is:

number of stackers = 8
number of work stations = 8
conveyor speed = 20 inches/sec.
conveyor length = 4680 inches

Some Optimum-seeking Rules

Since there are so many system performance measures, one needs a coherent framework within which to consider all of them in executing the system design. Indeed, it may not be possible to optimize all of the measures simultaneously. Combining several measures of performance into one objective function is referred to in the literature as the multiattribute objective function problem. It is a complex problem, and not well solved yet. The common alternative to using such combined objective functions is to select one measure to optimize and constrain the others to acceptable ranges. By performing sensitivity analysis on the constraints, one could readily determine the cost of altering them to improve the solution. This is the approach taken here.

The measure of performance selected for use with the heuristic rules is system throughput. Starting with an expected value model, the simulation model and heuristic rule progress toward a design configuration which satisfies the requirements for throughput. This approach is adopted as opposed to a large scale experimental design because the computer cost for simulating these complex systems is not trivial.

The initial optimum-seeking rules developed involve only two design variables: number of stackers and number of work stations. These were chosen since they were found to have the most impact on throughput [8]. Also, it was desired to keep the number of design variables to a minimum to facilitate programming and intuitive understanding of the heuristic performance. In effect, we are treating a three dimensional response surface defined by these two independent variables.

The heuristic rules are contained in a subroutine of the simulation model main program, and permit many iterations of the simulation, altering the number of work stations and stackers after each run according to a rule, and without user intervention.

Four simple rules are discussed and evaluated. All of them are based on the notion of the steepest ascent of a response surface: three in an unconstrained fashion, and one constrained. The direction of steepest ascent is usually determined through fitting a function to the response and using the calculus to determine slope [12]. However, our problem is so highly discretized that simply observing adjacent points works equally well.

The first three optimum-seeking rules deal with an unconstrained problem which may be described as follows: starting with the EVM output, find a solution with minimum, or near minimum, stackers and work stations for which the throughput is equal to or greater than the design throughput provided to the EVM model. The last rule treats a constrained problem which adds the requirement that the final solution shall also be equal to or less than some budgeted cost. Since cost data is difficult to obtain, the sum of stacker and work station idle time is used as a proxy for cost.

Rule 1 Starting with the simplex shown in Figure 2, make 9 simulation runs. Compare the EVM run with each of the other 8 and select the one with the largest throughput as the center of the simplex for the next iteration. If this leads to the choice of a previously selected combination of stackers and work stations, pick the second largest throughput. If more than one combination is equal to or greater than the

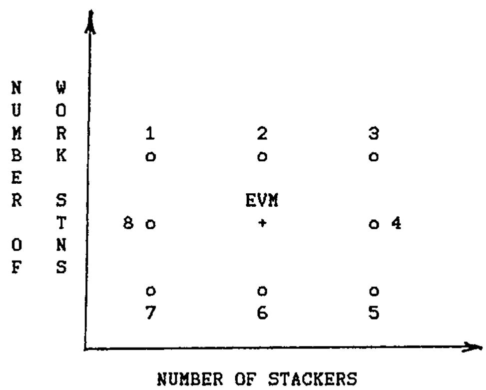

Figure 2. System Design Simplex

design throughput, select the smallest throughput which satisfies the design requirement.

The stopping conditions for Rule 1 are:

- o design throughput is attained
- o all candidtate designs in the simplex are less than the current design by 5% or more
- o a specified number of simulation runs has been made

Applying this rule to the illustrative system described above yields the results shown in Table 1.

Rule 2 This rule operates in the same way as Rule 1, but using a reduced simplex. To economize on the required number of simulation runs, points numbered 2, 4, 6, and 8 in Figure 2 are not considered. Thus, each iteration requires a maximum of 5 runs. The stopping conditions are the same as for Rule 1. The results of applying this rule are shown in Table 1.

Rule 3 Since most iterations of Rules 1 and 2 proceeded in the direction of increased numbers of stackers and work stations, the simplex was further reduced to the EVM run and the points numbered 2, 3, and 4 in Figure 2. This rule was first presented in [9]. The stopping conditions remain the same as for the other two rules. The results of applying Rule 2 are shown in Table 1.

Rule 4 This rule uses the original simplex of 9 points. It treats the constrained problem described above, and first examines the idle time of stackers and work stations before deciding if a candidate design is acceptable. Based on past experience with the model, a combined stacker and work station idleness of 60% was chosen as the maximum acceptable for a candidate. If this is exceeded, the next largest throughput is chosen. An additional stopping condition for Rule 4 is the situation in which all 8 candidtate designs violate the idleness constraint. The results from this rule appear in Table 1.

Evaluation of Optimum-seeking Rules

It can be seen from Table 1 that the solutions developed by the four rules vary widely in the characteristics of the systems produced as well as in the effort required to achieve the solutions. The number of simulation runs vary from 8 to 38, the system throughput ranges from 702 to 743 bins per hour, the number of stackers varies from 7 to 12, and the number of work stations, which show the least variability, run from 12 to 14. Rules 1 and 3 produced somewhat over-designed systems with throughputs of 730, and 743, respectively. Rules 2 and 4 produced designs with throughputs closer to the design requirment, 707 and 702, respectively. Also, Rule 4, which included an idle time constraint, did produce the system with the least combined idle time: 58%. However, it required more simulation runs than any other rule to do so.

Based on the limited experimentation with these rules thus far, it is not possible to conclude which are better than others. Rule 2 performed astonishingly well both in terms of the quality of the solution and the number of simulation runs needed to produce it. However, it surely benefited from a fortuitous starting point. Most "hill-climbing" approaches are very sensitive to both starting points and the nature of the response surface. Until more is known about the characteristics of the response surface for AS/RS systems, each heuristic rule should be applied using multiple starting solutions. In this case, points in the neighborhood of the EVM solution should be selected.

The idleness for work stations for designs produced by any of the rules is consistently 50% or more. Should not heuristic rules produce better systems? The cause of such high idleness is the congestion on the conveyor linking the stackers and work stations. The utilzation is 90% or more for all four system designs. The congestion could be alleviated by increasing the conveyor speed, but the value used is already near or at the practical maximum. It would appear that it is not possible to efficiently provide

Table 1. Summary of Optimum-seeking Rule Results

Rule	No. of Runs	Through-put	No. of Stackers	Stacker Idleness	No. of Work Stns.	Work Stn. Idleness
1	30	730	11	27%	14	53%
2	8	707	8	14%	12	50%
3	15	743	12	31%	14	51%
4	38	702	7	5%	14	53%

a throughput of 700 bins per hour without altering some other design attributes which decrease the transit time from stackers to work stations.

What can we conclude from these modest beginnings? It is clear that heurisitc rules can be applied to lead the designer from a tentative initial designs toward much improved ones. The conveyor imposes a clear upper limit on throughput. Because of practical limitations in increasing conveyor speed, this problem may require more innovative system designs, perhaps using multiple level conveyors or "short-circuiting" cross-overs to expedite the flow of bins in the system.

CONCLUSION

The work reported thus far on AS/RS systems such as the one modeled here, including this paper, represents only a modest beginning in the process of understanding the behavior of these complex systems. To design a truly cost effective system requires a far more detailed comprehension of design variables, operating policy variables, and their interaction on system performance. The effort reported here is continuing in that vein. The current direction involves the development and evaluation of more sophisticated optimum-seeking rules which include more design variables and a more complete response surface. The long range goal is to generate universal design rules which will yield cost effective systems without protracted, complex analysis.

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