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Intelligent control schemes for automated storage and retrieval systems

ABRAHAM SEIDMANN†

A new information system approach to the operational controls of automated storage and retrieval systems (AS/RS) is developed and examined. This approach is based on artificial intelligence, state-operator framework for problem solving. Gradually increasing the information level, several operational goal functions are identified for an industrial unit-load food produce AS/RS. These functions use real-time statistical interpolations to select the desired storage and retrieval bins. As a result the AS/RS response adapts itself to stochastic perturbations in the system conditions. Experimental evaluations using multiple variance analysis technique and detailed simulations have shown that the proposed dynamic approach is superior to the common industrial control method currently used in those industrial systems characterized by batch arrivals (and retrievals) of the UL's and non-stationary demand patterns. These evaluations further suggest that improved performance is realized with the increase in the information level. The operational control scheme developed in this paper appears to be an excellent control alternative for unit-load AS/RSs. This is due to its limited computational requirements and the augmented productivity as demonstrated here for a real case study.

1. Introduction

Automated storage and retrieval systems (AS/RS) are a combination of equipment and controls which automatically handles, stores and retrieves materials with great speed and accuracy (Tompkins and White 1984). Such complex systems may incorporate laser beam scanners, automated rollers, chain or overhead conveyors, computer controlled palletizers, weight and dimension checking stations, in-floor towlines, driverless tractors, or other automated links to the manufacturing or distribution facilities (White 1987). The entire operation is overseen by a supervisory computer which monitors the storage location of each item and its movements from one location to another (Hill 1980). These systems are used for storing raw parts, tools, in-process inventories and finished goods in conventional and flexible manufacturing systems (Sellers and Nof 1986, Arbel and Seidmann 1984).

In recent years, such systems have reached a point of maturity and economy (with rack supported structures depreciable as equipment). There are additional benefits to such systems: High floor and cube space utilization, improved material flow and inventory control and substantial saving in labour cost wherein AS/RS are justifiable as an alternative to conventional pallet rack warehousing (Rygh 1981). The AS/RS consists of storage racks, storage/retrieval crane, and input/output (I/O) pick-up and deposit station. Each crane operates in a single aisle with storage racks on either side. The crane has three mechanical drives: The vertical drive which raises and lowers the cargo, a horizontal drive, which moves the cargo back and forth along the aisle, and a shuttle drive, which transfers the cargo load between the

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† William E. Simon Graduate School of Business Administration, University of Rochester, Rochester, NY 14627, USA.

crane's carriage and both sides of the aisle. Typically, the horizontal and the vertical drives operate simultaneously in order to reduce the travel time.

A crane cycle generally begins with the crane at the I/O point; it picks up a load, travels to the storage location, deposits the load, travels empty (interleaves) to the retrieval location, retrieves the load, travels to the I/O point and deposits the load. The efficiency with which an AS/RS operates is influenced by the storage assignment, and by the picking policies. Storage policies refer to the assignment of arriving loads to an empty rack location. Picking rules consist of the determination of the load to be picked in a given cycle.

Previous research work in automated warehousing systems includes computer simulations, exact and approximate mathematical models. It is well known that dedicated storage, based on activity rates, can maximize the crane output. It may improve crane throughput because of the reduced space requirements (White 1980). On the other hand, randomized storage minimizes storage space, but reduces the crane throughput (Francis and White 1974). The selection of the appropriate storage method depends upon the weight given to storage space economy versus that given to throughput. The seminal paper of Hausman *et al.* (1976) formulates the merits of class-based storage assignment rules for single-aisle, no interleaving AS/RS. Later studies by these authors (Graves *et al.* 1977, Schwarz *et al.* 1978) examine several heuristic storage assignment interleaving policies assuming knowledge of the turnover time for the various items. The major performance measure investigated was the crane cycle time with mandatory interleaving.

The cube per order index rule (COI) for storage assignment was presented by Kallina (1977) and later studied by Wilson (1977). In two subsequent studies, Bozer *et al.* (1982) and Bozer and White (1984) extend the results presented by Graves *et al.* (1977) for a rack that is not necessarily square-in-time. They computed the crane throughput for two alternative operating policies and for three alternative I/O configurations. These studies were later used by Han *et al.* (1987) to develop lower bounds on the dual command cycle times and an effective nearest-neighbour heuristic. Other analytical studies are presented by Karasawa *et al.* (1980), Matson and White (1982), Ratliff and Rosenthal (1983), and by Kusiak *et al.* (1985). The paper by Kusiak *et al.* (1985) used dynamic programming formulations and a heuristic model to study the single-command order picking policy with due-dates.

The complexity of the AS/RS is such that existing analytical procedures do not have the capabilities to adequately model all their operational features (Maxwell 1981). As a result, simulation models are used to verify system specifications and to study system behaviour at stochastic dynamic environments. Bafna (1981) used simulation search technique to determine a minimum cost system design. A generalized manufacturing simulator (GEMs) for design verification is presented by Sathayi and Phillips (1979). Another simulator for automatic warehousing systems was developed by Ulgen and Elayat (1981). The optimal determination of the items to be picked during a single crane trip is presented by Elsayed (1981). Azadivar (1984) developed a simulation optimization approach aimed at finding the best way for allocating storage racks among items with various turnover times.

The simulated impact of seasonal trends on the crane activities was studied by Linn and Wysk (1987). They stress the importance of using a Pareto analysis for storage allocation at heavily utilized AS/RS. Moreover, they introduce a 'pursuit' mode for the crane by which it remains idle at the termination position of the last task waiting for a new command. Improved crane performance following this mode is shown. Recently, a hierarchical expert control scheme was presented by Wysk and Linn (1987). It uses a set of heuristic rules and short simulation runs to evaluate candidate control options. A combination of simulation and optimization techniques was also used by Roll and Rosenblatt (1981) to determine the desired warehouse capacity, configuration and storage policies.

Most of these studies assume static demand and arrival rates for all product types and that the stored pallets are retrieved based on a strict first in first out (FIFO) basis to ensure proper age control. In reality, the instantaneous and the long-run arrival or the demand rates fluctuate due to various short term random effects, seasonality effects, and changes in the corporate marketing strategy (Seidmann *et al.* 1985). Relaxing the stringent FIFO policy constraint, when operating a real AS/RS, might also prove useful. For instance, one may search for retrieval candidates among all products having the same age or expiry date. Moreover, with very few exceptions, these technical papers don't describe actual real-life applications comparing their data, assumptions and results with the current industrial practice and objectives.

The principal concern of this paper is to outline and examine the development of several control schemes for an AS/RS used by a national distribution centre of a certain producer. These control schemes are based on the state-operator framework for controlling intelligent systems (Nilsson 1980, Barr and Feigenbaum 1982). Following this approach we evaluate states of data and use operators which convert one state to another in order to reach a goal state. A state, in this case, is the data defining the state of the AS/RS at any general instant.

Following Bullers *et al.* (1980), a state variable is included in each state predicate to keep track of which of the facts are true in which state. Time is introduced to all predicates for which assertions of facts are dynamic. For each predicate involving time a complementary predicate denoting the negation of the original predicate was also introduced. Using such predicate/complement pairs state changes over time are modelled. This introduction of time necessitates another construct to permit dynamic inferences. Doing that one defines for each time-contained predicate a new predicate denoted as the current (latest) assertion of that time contained predicate; clearly, these two predicates have identical attributes. For example, a crane move is an operator which changes one state of the AS/RS into another. Operating the crane one needs a definition of an initial state, and of a goal state. One also needs structure which will decide in which order to try the operators, in order to solve the problem in a reasonable computation time. At any instant, the order of trying the operators is itself dependent on then current state of the data. In general, the aim of our program's control structure is to solve the problem with as little backtracking as possible.

Solving this finite-state, infinite-horizon undiscounted control problem we define several goal evaluation functions, which represent weighted 'cost' measures of the solution path, and then search for the least cost solutions. Increasing the information level, three such functions are developed. They operate with continuous statistical data interpolations to capture the AS/RS dynamics.

One way to proceed is to perform the operator computations using a formal deduction mechanism as embedded in a standard theorem prover. This is the approach used during the early stage of our research. But the real-time constraints of operating the industrial system, forced reduced computational requirements. Then, various heuristics, for ordering the operator applications in the state-space

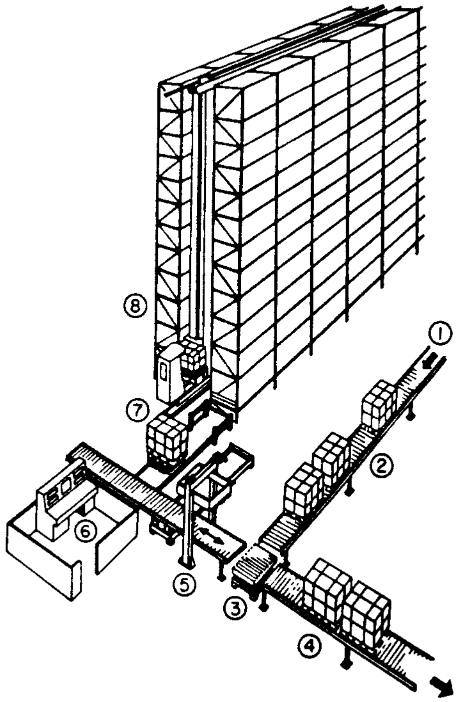

Figure 1. The distribution centre AS/RS studied in this paper: 1-input conveyor from plant, 2-accumulation conveyor, 3-turntable, 4-output conveyor from storage, 5-UL checking device, 6-control desk, 7-crane, 8-racks.

search, were used. The notation needed for these formulations is, unfortunately, cumbersome. For brevity, the details of the logic programming system and of the simulation models are omitted and we focus next on the quantitative aspects of the AS/RS model and on the composition and performance of the operational controls.

The structure of the paper is as follows: Section 2 presents the AS/RS studied here. The goal functions and the control schemes are given in § 3 and § 4 presents a summary of the experimental evaluations.

2. THE AS/RS studied

The AS/RS discussed here operates in a national distribution centre of a major dried food and pasta products manufacturer†. Finished products are containerized into special unit loads (UL) which are then hauled from the various production lines to this central distribution centre. Each UL consists of single product type. Following strict shelf-life controls the current management policy is to store these ULs for about 10 working days, and then to retrieve them back according to the standing orders of the various wholesalers. The AS/RS facility itself was designed and constructed by Demag AG (West Germany). It consists of a single aisle stacker with storage racks located at both sides. Figure 1 depicts a schematic structure of this system. Each rack consists of 14 rows and 95 columns. The total number of storage

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† Some minor technical details of this system were modified at the request of the above manufacturer which prefers them to remain unidentified.

locations is 2660 (= 2 × 14 × 95). Each location stores a single UL. All those locations have the same size, as are the UL's. Both incoming and outgoing UL's are transferred at the I/O point-located at the lower left corner of the racks.

All storage and retrieval requests are initiated with the crane at the I/O point. Each crane cycle consists of a storage task (ST), idle travel to the retrieval point (IT) and then a retrieval task (RT) terminating back at the I/O point. This operational mode is called 'dual-command' or 'interleaved' cycle. It is used during peak turnover periods, which are at the focus of our study.

Let I be the set of all UL types used here and $N = |I|$. The arrival rate of product type i ($i \in I$) into the AS/RS is observed to be Poisson with rate

$$\lambda_i = p_i \lambda \tag{1}$$

$$0 < p_i \text{ and } \sum_{i \in I} p_i = 1 \tag{2}$$

where p_i is the probability for UL of type i arrival and λ is the ergodic arrival rate. (λ = 230 UL/day). It has been shown by Schwarz *et al.* (1978) that the number of UL's in an AS/RS can be modelled as an $M|G|\infty$ queue (Kleinrock 1976). Recently Keilson and Seidmann (1987) studied the $M/G/\infty$ queue system where customers arrive at Poisson epochs of rate λ with random batch size and random *i.i.d.* storage times. A novel proof is presented showing that the ergodic distribution of the number of UL's in storage is a compound Poisson. It means that when the mean storage time for UL type i is μ_i days then the steady-state probability of n_i UL's is Poisson is with parameter $m_i = \lambda_i \mu_i$. In general, the storage periods are proportional to the arrival rates: UL's having the highest p_i values are stored for the shortest time intervals ('fast moving items').

Denote the average value of μ_i by μ and note that μ = 10 days. Since the total number of items in storage m is also Poisson with $m = \lambda\mu = 2300$ it's distribution is approximated by a normal distribution with a mean and variance equal to $\lambda\mu$. The required storage space for protection level of 99·9% against overflow is:

$$SC = m + 3{\cdot}090\sqrt{m} = 2448, \tag{3}$$

indicating that, with probability 0·999 there will be at least 212(=2660-2448) empty storage racks.

The size of the AS/RS and the crane speed are given by:

V_h = horizontal speed = 180 (fpm)
V_v = vertical speed = 90 (fpm)
H = rack height = 63 (ft)
L = rack length = 285 (ft)
$t_h = L/V_h$ = time to reach the end of the rack = 1·58 (min)
$t_v = H/V_v$ = time to reach the top of the rack = 0·7 (min)

Each crane cycle starts and terminates at the I/O point which has coordinates (0, 0). The three serial legs composing the cycle are (Fig. 2):

I delivering an arriving UL from the I/O point to an empty bin (with coordinates [a, b]),

II travelling from the storage bin to the required retrieval bin (with coordinate [c, d]), and

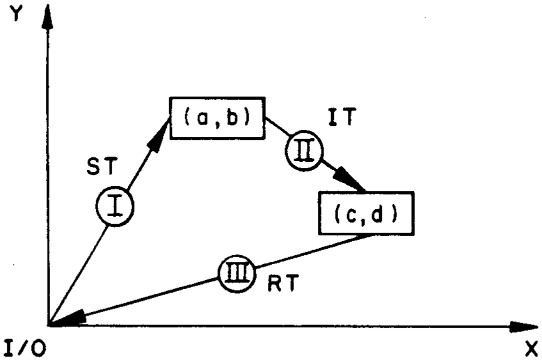

Figure 2. Dual-command cycle: Store at (*a*, *b*) and retrieve from (*c*, *d*).

III delivery of the retrieved UL back to the I/O point.

The cycle travel time CT is computed as:

$$CT = t_{\mathrm{ST}} + t_{\mathrm{IT}} + t_{\mathrm{RT}}, \tag{4}$$

with each leg given by:

$$t_{\mathrm{ST}} = \mathrm{Max}\left\{\frac{a}{V_{\mathrm{h}}}, \frac{b}{V_{\mathrm{v}}}\right\} \tag{5}$$

$$t_{\mathrm{IT}} = \mathrm{Max}\left\{\frac{|c-a|}{V_{\mathrm{h}}}, \frac{|d-b|}{V_{\mathrm{v}}}\right\} \tag{6}$$

$$t_{\mathrm{RT}} = \mathrm{Max}\left\{\frac{c}{V_{\mathrm{h}}}, \frac{d}{V_{\mathrm{v}}}\right\} \tag{7}$$

Assuming ('travel time') uniform distribution of the UL's over the storage space and using FIFO one can easily verify that the expected value of CT is:

$$E(CT) = [\tfrac{5}{3} + \tfrac{4}{6}B^2 - \tfrac{1}{15}B^3] \quad \mathrm{Max}\,(t_{\mathrm{h}}, t_{\mathrm{v}}) \tag{8}$$

where

$$B = \min\left(\frac{t_{\mathrm{h}}}{\max\,(t_{\mathrm{h}}, t_{\mathrm{v}})}, \frac{t_{\mathrm{v}}}{\max\,(t_{\mathrm{h}}, t_{\mathrm{v}})}\right) \tag{9}$$

In our case we find that

$$B = 0{\cdot}44, \text{ and } E(CT) = 2{\cdot}84 \text{ (min)}.$$

This FCFS cycle time might be reduced through the use of a more intelligent control scheme which considers the relative locations of the empty bins and the various candidate ULs to be retrieved. The actual time required by the crane to seize or to deposit a UL is in the order of ten seconds per cycle, and slightly reduces the crane capacity. Being a constant it is not affected by the AS/RS control scheme.

The current practice at the AS/RS (denoted as DC—default control) was to store arriving UL's at the closest available (empty) bin and then to retrieve the first UL type from the computerized retrieval list. ULs were retrieved according to a FIFO scheme in order to minimize the variance of the storage times. Since several ULs of type k typically arrive at the same day one can permute the retrieval sequence within the same age group without violating the age control policy. During our study, management policy was even modified allowing for the retrieval logic to scan the retrieval candidates among the oldest ULs as well as those arriving one or two days later than the oldest item in storage.

The relative reduction in t_{IT} using the shortest distance among r_i candidates retrieval locations for UL type i and y empty bins-rather than FIFO is explored next.

The distance between two randomly selected UL locations is a random variable, Z, with probability density function $f(z)$ and cumulative probability function $F(z)$:

$$f(z)=\begin{cases}(2-2z)\left[2\left(\frac{z}{B}\right)-\left(\frac{z}{B}\right)^2\right] & 0\leqslant z\leqslant B\\ \quad+(2z-z^2)\left[\frac{2}{B}-\frac{2z}{B^2}\right] & \\ 2(1-z) & B<z\leqslant 1\end{cases}\tag{10}$$

$$F(z)=\begin{cases}(2z-z^2)\left[2\left(\frac{z}{B}\right)-\left(\frac{z}{B}\right)^2\right] & 0\leqslant z\leqslant B\\ 2z-z^2 & B<z\leqslant 1\end{cases}\tag{11}$$

(This assumes that the *full* rack is used under random storage.)

At each cycle there are r_i, type i UL's for retrieval. Searching among all UL's type i with the same arrival date means that r_i has a Poisson distribution with mean $p_i\lambda$. The expected value of $Z_1^{r_i}$—the smallest order statistic (reflecting the distance to the nearest-neighbour bin) of a sample of size r_i is (Hogg and Tanis 1977):

$$E(Z_1^{r_i})=\int_0^1 z(r_i)[1-F(z)]^{r_i-1}f(z)\,\mathrm{d}z\tag{12}$$

Unconditioning on r_i leads to

$$E(Z_1^i)=\int_0^1\sum_{r_i=0}^{\infty} z(r_i)[1-F(z)]^{r_i-1}\frac{(\lambda p_i)^{r_i}}{r_i!}\exp^{-p_i\lambda}f(z)\,\mathrm{d}z\tag{13}$$

and clearly

$$E(t_{\mathrm{IT}})=\sum_{i\in I}p_i\,E(Z_1^i)\tag{14}$$

Note that our new model (eqns (13) and (14)) extends the earlier expressions given by Bozer and White (1987) and by Han *et al.* (1987) so that one can now handle the case of a *randomly distributed* sample size r_i. Equations (13) and (14) were numerically evaluated by us (for finite r_i values) using IMSL/DMLIN routine for gaussian tensor product integrals.

Comparing the $E(t_{\mathrm{IT}})$ results as computed in eqn (14) for this system against the FCFS values of $E(t_{\mathrm{IT}})$, as given by Bozer and White (1984), indicated an overall potential for crane cycle time reduction of about 18–25%. These estimates were then validated against detailed simulations of the above system (Zillbiger and Seidmann 1984). Realizing these savings means that for each of type i UL to be retrieved one must look for all the UL type i in storage having the proper age for retrieval and then find the closest empty bin for the storage leg of the crane. Furthermore, the system dynamic is such that the sample size (being the number of empty bins plus the

r_i value) is typically 50 or above. When operating under heavy storage load there are many type i UL's in storage (with only few empty bins); on the other hand, when the storage load reduces then there are many more empty bins (with fewer type i candidates). In those cases one may search through the retrieval file looking for other retrieval requests that may result in improved cycle design. Those observations formed the basis of the retrieval rules described in the next section.

3. The AS/RS controls

3.1. *The solution strategy*

Given the enormous computational requirements posed by standard techniques as applied to AS/RS an effective (but not guaranteed to be optimal) AI approach has been selected. The crane cycles are planned one-at-a-time in a real-time basis. The goal state as well as the initial state are unknown before every crane cycle and a forward search determines the decision variables. In this case the decision variables are the storage bin (i), the UL type to retrieved (k), and the actual retrieval bin (j)—when several type k ULs are available in storage.

This problem is a discrete multi-stage decision problem. The values of the decision variables define the state of the system. Thus system state is constantly being monitored during the solution process (and the AS/RS operations) by changing some of these variables. This characteristic of changing the system state through the changes of variables is basic to the state-operator scheme. In classical AI approaches, the state description is given formally in first order logic. The problem is then solved in state-operator framework using Prolog to represent the elements, the attributes and their relationships in the AS/RS.

Prolog is a programming language based on symbolic logic, developed at the University of Marseille as a partial tool for logic programming. It is based on the idea that statements in first-order predicate logic, cast in Horn clause form, can be used directly as a programming language. In Horn clause form, one conclusion is followed by zero or more conditions, as follows:

> 'Conclusion < —condition 1, condition 2, condition 3 . . . condition N.' The whole clause can be read: The conclusion is true if condition 1 and condition 2 and . . . condition N are all true.

A clause is called a fact when the number of conditions is zero, otherwise it is called a rule. Each program in Prolog consists of rules and facts which represent the hypotheses about the world, and our questions are theorems that we would like to have proved. This enables the user of the computer to input only the facts and rules for the problem he wants to solve, and not be concerned how it is executed by the machine.

The search for the solutions to our problem was first done by Prolog (depth first search). The state-space was reduced by limiting the depth search in the retrieval file. (This point is further discussed in § 3.2).

This search is directed by three control functions which are discussed next. Going from the first function to the second and then to the third one increases the knowledge level of the controller (and the computational effort per state) as well as the resulting AS/RS effectiveness.

A rule-based system is used to enforce certain management constraints on these control functions (Kusiak 1987). These constraints include safety, dietary and perishability considerations. For example:

Rule R_1: *If*: item k has to be retrieved
Then the candidate ULs are those stored more than SL^k days (SL^k is an age-control management parameter).
If: there are no candidate ULs stored more than SL^k days
Then: search among all other type k ULs.

Defining the storage data structures let: T_j = the UL type in bin j, B_k = the set of all bin locations of UL's type k, R = the ordered retrieval set, and Y = the set of empty bins.

3.2. *The basic control function*

The basic control function has three components. Each one of those components affects the system performance in a distinct manner. The linear combination of these compact performance measures attempts at producing the required long-term response pattern. If the crane stores a UL at i and retrieves one from j then the basic control function (BC) is:

$$\text{Min } \{F_1(D_j, S_j, E_{ij})\} \qquad T_j \in R,\ i \in Y$$

where

$$F_1(D_j, E_{ij}) = \alpha_1 D_j + \alpha_2 S_j + \alpha_3 E_{ij} \tag{15}$$

S.T.:

$$S_j \leqslant \text{Min } \{S_{B_k}\} + 2 \qquad k = T_j \tag{16}$$

$0 \leqslant \alpha_z$, $z = 1, 2, 3$ are the tuning coefficients used in order to track the relative significance of the control variables. The causal effects of these tuning coefficients are depicted in § 4.4.

D_j = the distance of (candidate) retrieval bin (j) from the I/O point,

S_j = the arrival time to storage of the UL in bin j, and

E_{ij} = the cycle 'effectiveness' measure if the crane stores a UL at i and retrieves one from j.

The procedure used for computing D_j, S_j and E_{ij} are described next.

The retrieval distance (D_j) has an immediate effect on the cycle length attempting at minimal values to reduce the crane travel time. The travel times at the two axes are independent of each other since each axis has an independent motor. Hence, we are not interested in the relative distances but at the chevychevian distances of the various bins from the I/O point as explained in § 2.

The difference between the current time and the arrival time to storage (S_j) measures the shelf life of the produce in storage. An important consideration in our system is the elimination of those instances where UL assigned to remote storage bins are left over there for extended time periods. It means, therefore that certain retrieval priority is assigned according to the UL's current storage time. Such a priority is given to UL's with earlier arrivals to the storage bins. The lower bounds (eqn. (16)) on S_j are enforcing the management age control policy as described earlier. Strictly following the minimal S_j rule for selecting the retrieval bin means using a FIFO logic. The measurement unit used for S_j is storage time in days. The

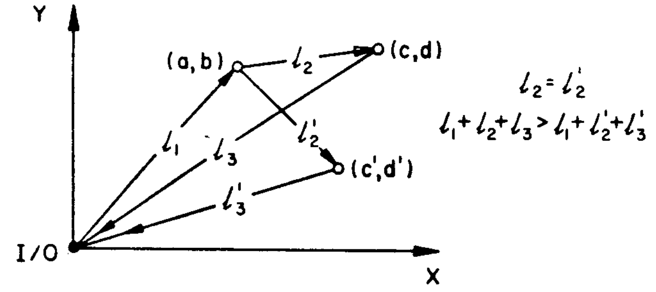

Figure 3. Two hypothetical crane cycle with distinct E_{ij} values.

long term effects of the crane tours are measured by the cycle effectiveness measure (E_{ij}). Its objective is to drive the crane into making the most out of each cycle travelled. Doing so it strives at storing and retrieving a UL from closeby bins. Whenever the crane travels to store a UL at a remote storage bin it attempts at trying to combine that long travel leg with a UL retrieval from that remote neighbourhood.

The computational procedure for E_{ij} is illustrated by the following example. Consider two hypothetical cycles (Fig. 3): One which goes from (0, 0) to (a, b), (c, d) and back to (0, 0) with a length of $L(=l_1 + l_2, + l_3)$ and another which goes from (0, 0) to (a, b), (c', d') and back to (0, 0) with a length of $L' = (l_1 + l'_2 + l'_3)$. Here we assume $l'_2 = l_2$. Observing Fig. 3 it becomes clear that for the same l_1 and that for $l_2 = l'_2$ the cycle length increases as the retrieval bin furthers away from the I/O point. This phenomenon leads to the following definition of E_{ij} as 'the additional path to be taken, beyond the storage bin, as compared with immediately returning to the I/O point'.

Following the two cycles as depicted in Fig. 3 it is clear that

$$E_{ij} = l_2 + l_3 - l_1 < E'_{ij} = l'_2 + l'_3 - l'_1 \tag{17}$$

Initial experimentation with this cycle effectiveness measure resulted in unbalanced crane load. As a result the following heuristic correction term is added to E_{ij} to accommodate those cases where the retrieval bin lies on, or very close to, the return path (Fig. 4).

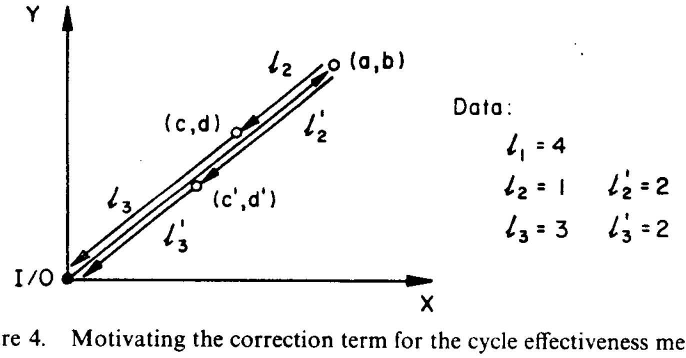

Figure 4. Motivating the correction term for the cycle effectiveness measure.

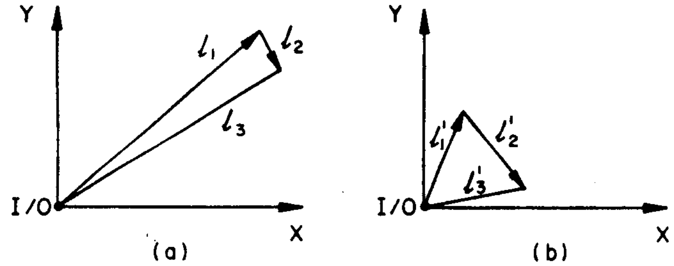

Figure 5. (*a*) An 'effective' cycle space. (*b*) A futile cycle. (Assuming: $l_1 + l_2 + l_3 = l'_1 + l'_2 + l'_3$).

Doing so let us redefine E_{ij} as:

$$E_{ij} = [\text{the additional path to be taken}] + [\text{preference to neighbouring bins}]$$
$$= [l_2 + l_3 - l_1] + [l_2] = 2l_2 + l_3 - l_1$$

The performance of the E_{ij} measure is illustrated next. Consider a cycle with a storage to be made at (*a*, *b*) and two options for a retrieval (Fig. 4) along the return path (*c*, *d*) or (*c*′, *d*′). The equivalent distances are $l_1 = 4$, $l_2 = 1$, $l_3 = 3$, $l_2 = 2$ and $l_3 = 2$. The effectiveness measure for the two optional cycles are:

$$E = 2l_2 + l_3 - l_1 = 2 + 3 - 4 = 1$$
$$E' = 2l'_2 + l'_3 - l'_1 = 4 + 2 - 4 = 2$$

Since Min $\{E, E'\} = 1$ the preferred cycle is the one using (*c*, *d*) for retrieval. It might be argued for the crane to retrieve the UL from (*c*′, *d*′) and thus to open a new empty bin there. **However, improved performance is observed when the crane spends most of its time in the locus closer to the I/O.** Therefore, if a long leg is required the correction term used in (E_{ij}) maximizes its effectiveness. As a rule, longer but effective cycles (Fig. 5 (*a*)) are preferred to short futile cycles (Fig. 5 (*b*)).

The controller computes the values of $F_t(D_j, S_j, E_{ij})$ for all the feasible cycles for each one of the items in the retrieval file R at time t. These computations are carried out as a function of the UL type to be stored. Specifically, D_j is given by the bin being evaluated, S_j is given by the arrival time of the UL to bin j, and E_{ij} is computed by searching among all the *closest* empty bins around the candidate bin (j) for retrieval.

Example

Consider a case (Fig. 6) where the retrieval request file, R is given by:

Rank	Type	UL quantity
1	*X*	5
2	*Y*	3

The UL types to be retrieved at the cycle can be either X or Y. Figure 6 shows the storage locations and the storage entry date for ULs type X and Y in storage. The speed ratio is $V_h = 2V_v$. The cycle costs computations from the six feasible retrieval bins are detailed in Table 1. The minimum cost cycle calls for storing the new UL at (2, 3) and for retrieving UL type Y from (5, 4).

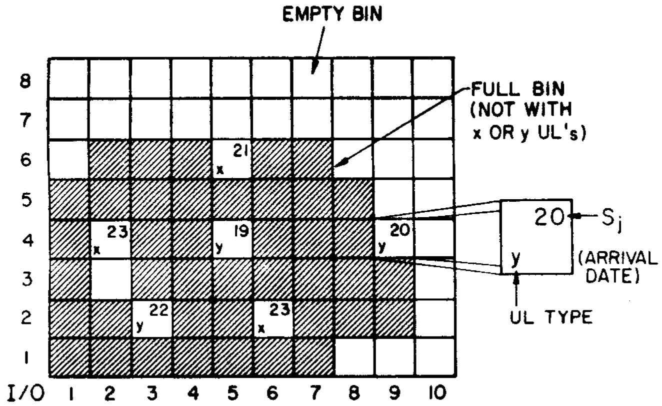

Figure 6. Sample computations of the control function F_{I}.

In the above example all the entries in the R file were examined. In reality this file contains simultaneous requests for many more part types. We investigated the impact of increasing the search depth in R on the system performance. The initial results show a significant improvement when the depth search in R is increased from 1 to 2 and no significant improvements thereafter. A probable explanation might be that following this control policy the various UL types and the empty bins are distributed throughout the storage area. As a result, the steady state response is likely to be the same for most types at the retrieval request file. Also the study of Han *et al.* (1987) and our analysis using eqn. (13) indicate that only minimal marginal benefits can be realized when the sample size is increased beyond 20. Given the item population, and the number of empty bins, this value is reached fairly early during our search.

3.3. *The adaptive control function*

Increasing the information level of the system controller an adaptive control function (AC) was explored. It was designed to better operate the AS/RS in a time-varying environment. If the internal parameters of the system are fixed, as in the case of the BC function, the system might operate quite differently in one

				Retrieve from:		
F_{I}	D_j	S_j	E_{ij}	Type	Bin	Store at
33	8	23	2	X	(2, 4)	(2, 3)
39	12	21	6	X	(5, 6)	(5, 7)
35	6	23	6	X	(6, 2)	(8, 1)
32	4	22	6	Y	(3, 2)	(2, 3)
31	8	19	4	Y	(5, 4)	(2, 3)
33	9	20	4	Y	(9, 4)	(10, 4)

Note: The distance values are expressed in the equivalent number of bins along the fastest (horizontal) axes. In this simplified example the bins have square shape.

Table 1. Evaluating the Feasible cycle costs for $\alpha_1 = \alpha_1 = \alpha_3 = 1$.

environment than it should in another. The AC function is designed to compensate for some dimensions of the changing environment by monitoring the AS/RS performance and altering, accordingly, some parameters of its control functions to gain improved performance. This control scheme changes the policy decision on a real time basis as a function of the *number* of orders on the retrieval queue at the time t, $N(t)$, $N(t) = 0, 1, 2, \ldots$. Adding this knowledge component means that the relative importance of the retrieval distance component increases with the increase in the retrieval queue length; this results in the AS/RS attempting at reducing $N(t)$ by retrieving UL stored closer to the I/O point. Consequently, the crane cycle times are shortened leading to the desired transient decrease in $N(t)$.

On the other hand, at times when $N(t)$ is relatively small the immediate cycle performance is given inferior priority—as compared with the other operational parameters (i.e., D_j and S_j) which pander to the long-term objectives of system effectiveness.

The AC function is

$$\text{Min } \{F_{\text{II}}(D_j, S_j, E_{ij}, N(t))\} \qquad T_j \in R,\ i \in Y \tag{18}$$

where

$$F_{\text{II}}(D_j, S_j, E_{ij}, N(t)) = \alpha_1 N(t) D_j + \alpha_2 S_j + \alpha_3 E_{ij} \tag{19}$$

S.T.:

$$S_j \leqslant \text{Min } \{S_{B_k}\} + 2 \qquad k = T_j \tag{20}$$

Experimental evaluations of this function are provided in the next section.

3.4. *The dynamic adaptive control function*

The dynamic adaptive control structure (DAC) is designed in order to handle another fundamental AS/RS management issue. This is the storage assignment problem where different product groups have different arrival rates and, moreover, these rates tend to vary dynamically as a result of several reasons. These reasons include seasonal changes in the customer's taste, introduction of new products varieties and special sales campaign typically aimed at increasing the sales level of slow moving items. The proposed dynamic adaptive control (DAC) scheme delineated below is designed to capture these changes in the mean values of the arrival (and retrieval) rates and to reflect them in the operational mode of the AS/RS. The basic idea is to modify the control structure in such a way that UL's of products having higher traffic intensity will be stored closer to the I/O point (Hausman *et al.* 1976).

The average storage time for UL type k is computed dynamically whenever such a type k UL leaves the AS/RS. The time average for storage of type k ULs at time t is denoted as $A_k(t)$. Fast moving ULs will have smaller values of $A_k(t)$.

It has been shown by Hardy *et al.* (1949) that the cross product of two series (in our case the travel time to bin i, ($i \in Y$) which is the storage location for an arriving type k-D_i^k and $1/A_k(t)$) is minimized when these series are monotonic in antithetical senses (i.e., one series is non increasing and the other is non-decreasing). Hence, the time average ratio of $[D_i^k/A_k(t)]$ is minimized when slow moving items (smaller $1/A_k(t)$) are stored further away from the I/O point (larger D_i^k) and the fast moving items (smaller $A_k(t)$)—closer to the I/O point.

These foregoing arguments lead to the following dynamic adaptive control (DAC) function:

$$\text{Min } \{F_{\text{III}}(D_i^k, D_j, S_j, E_{ij}, N(t), A_k(t))\} \qquad T_j \in R,\ i \in Y \tag{21}$$

Where

$$F_{\text{III}} = \alpha_1 N(t) D_j + \alpha_2 S_j + \alpha_3 E_{ij} + \alpha_4 \left[\frac{D_i^k}{A_k(t)}\right] \tag{22}$$

$$S_j \leqslant \text{Min } \{S_{B_k}\} + 2 \qquad k = T_j \tag{23}$$

Note that the forth component of F_{III} facilitates the dynamics of the storage allocation decisions.

4. Experimental evaluations

4.1. *Background*

This section presents the methodology used for evaluating the performance of the control schemes proposed earlier. Evaluating control alternatives in our case is a complex task because of the numerous control parameters and performance measures that influence the final results. Therefore, a digital simulation model, that allows for detailed examination of those parameters was developed. Operational data was collected for 12 months at the AS/RS facility. It was then used to generate the simulated arrival processes, the retrieval requests and the storage times. The results of the simulation runs were analysed using multivariate analysis of variance program (MANOVA) and an ordinal ranking procedure (RANK). This procedure was applied first to evaluate the parameters of the heuristic solution algorithm and then to compare the various control schemes.

Next a few definitions of the major performance measures are introduced:

1. The maximal number of items on the retrieval queue, MQOUT.
2. The average waiting time per items on the retrieval queue, AQOUT.
3. The average travel time for the crane from the I/O point to the storage bin, TRAVC.
4. The asymptotic percent idle-time of the crane, PIDLE.

The first two performance measures (MQOUT, AQOUT) attempt at estimating the system responsiveness to varying retrieval loads from the system, the third one (TRAVC) points at the magnitudes of actual changes in the storage assignment modes and the last one (PIDLE) measures the utilization of the bottleneck resource.

Other performance measures such as the average and the maximal values of the waiting times in the input queues or the average and the variance of the time in storage were also considered. The response pattern associated with these additional measures was similar to that of the first four measures. For brevity, therefore, they are not further discussed.

4.2. *The MANOVA model*

Each experimental *group* was associated with a given operational scenario. That scenario defined the operational control scheme to be used (i.e., DC, BC, AC or

DAC) as well as the values of the control parameters (α_z, $z = 1, \ldots, 4$). Several random number streams were used to generate replicated observations for each group. Each run resulted in a recorded set of p performances measures. The basic linear model used is:

$$\mathbf{Y}(n^*p) = \mathbf{X}(m^*n)\mathbf{B}(m^*p) + \mathbf{E}(n^*p) \tag{24}$$

Where: $\mathbf{Y}$ is observed simulation responses (MQOUT, AQOUT, TRAVC, PIDLE) using the above four control schemes, $\mathbf{X}$ is experimental design matrix, $\mathbf{B}$ is parameter matrix (the 'control parameters treatment' effects), $\mathbf{E}$ is random error matrix, n is total number of observations, p is number of dependant parameters, and m is number of parameters.

The random errors are assumed to be independent with p- variate normal distribution having mean $\mathbf{0}$ and a covariance matrix $\mathbf{S}$. It is known that as long as $\mathbf{S}$ is positive definite, the covariance of $\mathbf{Y}$ can have any pattern (Harris 1975). The rows of $\mathbf{X}$ are identical for all the members of the same experimental group. This leads to the reduced average cell model:

$$\mathbf{Y}^*(g^*p) = \mathbf{A}^*(g^*m)\mathbf{B}(m^*p) + \mathbf{E}^*(g^*) \tag{21}$$

where g is number of groups, $\mathbf{Y}^*$ is mean group response matrix, $\mathbf{E}^*$ is mean group residual, and $\mathbf{A}^*$ is the parameter matrix of the model computed from

$$\mathbf{A}^*(g^*n) = \mathbf{K}(g^*r)\mathbf{L}(r^*m) \tag{26}$$

with $\mathbf{K}$ is column basis, $\mathbf{L}$ is contrast coefficients, or the raw basis, and r is rank of $\mathbf{K}$ and $\mathbf{L}$.

Significance tests in multivariate analysis of variance models are based on functions of the eigenvalues of the error cross products matrix. Both Pillai's criterion and Wilk's Lambda significance tests were used. A detailed comparison of the powers of these two tests is presented by Morrison (1967). Having concluded that there is a significant difference in the response means due to the control scheme effects the Newman-Keuls range tests were used to test for means differences.

Table 2 presents a sample output of the MANOVA test procedure used for comparing the DC vs. the BC schemes. All other tables are omitted in the forthcoming sections. The detailed results presented next have significant control scheme effects ($\alpha < 0{\cdot}05$). Mean differences displayed are also significant ($\alpha < 0{\cdot}05$).

4.3. *The RANK procedure*

Ordinal performance ranking of the four control schemes were computed whenever the MANOVA analysis detected significant control effects on the four major performance measures outlined in § 4.2. The objective was to attempt at computing a proxy value function indicating the relative preference of one control scheme over the other. The relative ranks values computed for each data set are used merely for ordinal ranking relative to the originating experimental design. Unlike nominal rank values they can't be used for cross comparisons.

The rank computations are conducted by linearly transforming the computed performance measures to a 0-1 scale. Using this scale, 1-corresponds with the best result and 0-with the worst result observed for a given performance measure at a particular experimental setting. Doing so for each group of performance measures leads to the average rank for each control scheme using a prescribed set of control

Effect: groups

Test name	Value	Exact F	Hypoth. dferror. df		Significance of F
Pillai	0·97961	19·22169	5·00	2·00	0·04901
Wilks	0·02039	19·22169	5·00	2·00	0·04901

Eigenvalues and canonical correlations

Root No.	Eigenvalue	Canonical cor.	Squared cor.
1	48·05423	0·98975	0·97961

Dimension reduction analysis

Root No.	Wilks lambda	F	Significance of F
1	0·02039	19·22169	0·04901

Univariate F tests with (1, 6) df

Variable	Hypoth. SS	Error. MS	Hypoth. M	Error. MS	F	Significance of F
$X1$	2709·95220	6879·98555	2709·95220	1146·66426	2·36334	0·17513
$X2$	5100·50000	8775·5100	0·50000	1462·58333	3·48732	0·11107
$X3$	6·71611	9·58998	6·71611	1·59837	4·20196	0·08626
$X4$	1·25611	20·15378	1·25611	3·35896	0·37396	0·56329
$X5$	7·46911	2·87437	7·46911	0·47906	15·59110	0·00755

Table 2. MANOVA results for control scheme effects for six performance measures: DC vs. BC.

parameters. These average ranks vary between 0 and 1, where higher ranks indicate higher endorsement levels.

4.4. *Comparative evaluations*

The parameters of the control function (α_z, $z = 1, \ldots, 4$) affect the operational responsiveness of the system. Numerous experiments were conducted in order to gain some insight into the sensitivity of the control function to the relative changes in these parameters. Other objectives included the deletion of irrelevant combinations and steering the system response in accordance with the given management priorities.

Table 3 and Fig. 7 illustrate the causal effects the relative values of α_z have on the system performance using BC scheme. It can be seen, for instance, that in Case 2 the crane is directed at using the closest bins for storing and retrieving UL's thereby deriving a significant increase of the time in storage variance. Contrarily, the time in storage variance is reduced in cases 7 and 9 where α_z is assigned relatively higher values. These experiments indicate that tuning the control parameters may lead to superior performance for a given set of operational requirements.

Case	α_1	α_2	α_3
1	1	0	2
2	1	0	1
3	3	2	1
4	2	1	1
5	1	1	1
6	0	1	1
7	1	2	0
8	1	2	1
9	1	3	2

Table 3. Control parameters used in BC ordinal ranking experiments.

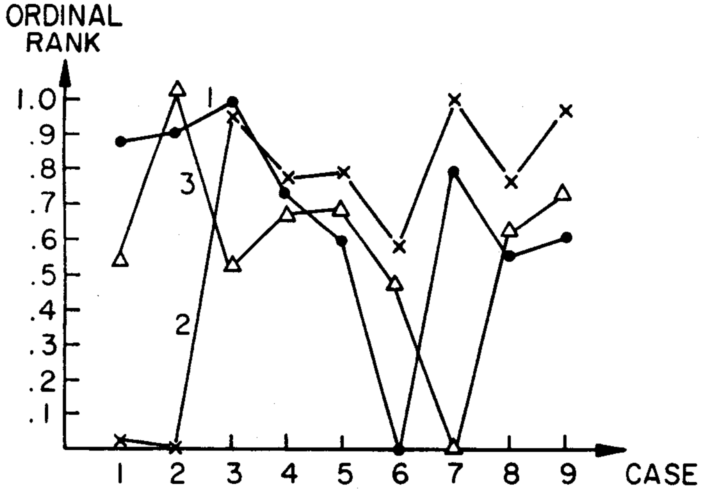

Figure 7. Ordinal ranked responses of three performance measures for nine combinations of α_z: 1-mean distance between I/O and storage bin, 2-variance of storage time (within UL types), 3-mean cycle time.

Next, the various control schemes are compared. Recall that only significant differences ($\alpha < 0{\cdot}05$) are presented. We start by comparing default control (DC) as used by the AS/RS vendor vs. basic control (BC). Four experimental groups of the BC were evaluated against the DC. The parameters sets used are given in Table 4 and the relative improvements are given in Table 5.

The increase in crane idle time, as given in Table 5 is a result of improved system schedule using the BC. This also leads to reductions in the maximal retrieval queues and the average waiting times for retrieval. The slight increase (3.6%) in the crane travel time from I/O to storage is expected since the DC directs the crane at storing UL's in the nearest empty bin.

Table 5 also presents the comparative results of AC vs BC and of AC vs. DC. Using AC further improves the system performance through reductions in the retrieval queues. This means improved logistical service. The increased crane idle times mean that the same crane can handle augmented traffic volume.

Finally, the performance of the Dynamic Adaptive Control (DAC) function was investigated for a case where the arrival rate of the ULs was dynamically modified. Our objective was to detect the sensitivity of the DAC scheme to changes in the steady-state arrival rates of the various product types. Properly operating, DAC should respond by changing the storage allocating scheme such that the faster moving items are stored closer to the I/O. Doing so the system was first simulated using the original arrival pattern. Following a simulation of 400 operating hours the

Group	α_1	α_2	α_3
1	1	0	2
2	1	0	1
3	3	2	1
4	2	1	1

Table 4. Parameters sets for comparing BC vs. DC.

	Improvement (%)		
Performance measure	BC/DC	AC/BC	AC/DC
1. MQOUT—Maximal retrieval queue	29·2	32·9	67·8
2. AQOUT—Average waiting time for retrieval	51·4	41·6	71·6
3. TRAVC—Crane travel time from I/O to storage	−3·6	8·2	4·8
4. PIDLE—Crane idle time	273·2	75·0	55·3

Table 5. Comparing relative performance improvements.

arrival pattern was reversed; the p_i values and the storage times of the fastest moving items were assigned to slowest moving items and so on. This new arrival rate structure was used for a similar time period.

Implementing the DAC scheme leads to a new storage allocation mode of the ULs as they get into the system. It is clear from Table 6 that following this change in the arrival pattern the average storage distance for the Class A products increased while a decline in average storage distance is recorded for the class D products.

The impact on the system performance is illustrated by Table 7. The results underscore the superiority of the 'knowledge based' DAC over the default control (DC) control or over the adaptive control (AC) schemes which ignore the dynamics of the underlying changes in the relative arrival rates of the various UL types. In

	Original arrival distribution function	Modified arrival distribution function
UL type number	Average distance from I/O	Average distance from I/O
1	18	46
2	45	51
3	48	52
4	23	57
5	40	66
⋮		
20	29	26
21	75	21
22	33	33
23	77	51
24	82	13

Table 6. Storage allocation and the average time in storage for selected UL types.

	Improvement (%)	
Performance measure	DAC/DC	DAC/AC
1. MQOUT	47·1	22·8
2. AQOUT	70·7	50·5
3. TRAVC	11·7	6·9
4. PIDLE	670·0	434·0

Table 7. Relative performance improvements with non-stationary arrival pattern and reallocation of storage zones.

fact, using the DC the crane was utilized at about 97% of the time. Such a high utilization rate indicates that there is no spare capacity for future increase in the UL traffic intensity.

5. Conclusions

The research results presented in this paper demonstrate that proper extensions of the state-operator methodology can be implemented in modelling and later controlling of AS/RS in a dynamic operational environment. It is shown that the proposed approach which uses generalized goal functions for state transition evaluations is superior to the one currently proposed by various system vendors. Comparison with other published models is not presented since mostly all of them are based on either restrictive assumptions to sustain mathematical tractability or on case-specific performance measures. For example, the analytical models presented so far assume stationary distribution of the arrival rates (no seasonality) and that there is no choice among the candidate UL's to be retrieved in a given cycle. These restrictive assumption are relaxed in our study.

Three goal functions were developed step by step, while increasing the information level: The first function is a weighted combination of variables that indicates the correspondence of a specific cycle to the desired policy. The second one is a generalization of the first one: It dynamically updates coefficient weights in the goal function, utilizing more information about the system status to actually adapt the policy in real time. The third goal function further generalizes the second model: It includes a variable argument that deals with dynamic location assignment of items in the warehouse. Location assignment means remote storage of items that have a slow turnover rate, and storing fast moving items in the vicinity of the I/O port. These goal functions use continuous statistical interpolation (dynamically produced), to make the proper rack assignments and retrievals. Each increase in the information level lead to an additional improvement in the AS/RS performance as measured for instance, by the crane throughput and the retrieval queue length.

With the advent of computer integrated manufacturing, and its accompanying technological advantages one can use this scheme in a hierarchical control context. Doing so, the higher level controllers will vary the weighting factors (α_z) to reflect instantaneous plant needs. As our empirical results show, the idea of dynamically updating the control functions in real-time AS/RS operations is also a promising research direction. Our results also indicate that much research remains to be done. For example, we didn't attempt to find the best combination of the weighting factors, we didn't attempt to find the best way to aggregate the information levels, nor did we attempt to develop an automated approach to implement higher level of learning or knowledge acquisition. Further studies of these issues are likely to lead to even better control structures.

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Une nouvelle approche de système d'information pour les contrôles opérationnels de Stockage Automatisé et des Systèmes de Retraits (AS/RS) est développée et examinée. Cette approche est fondée sur l'Intelligence Artificielle, logiciel intégré pour la résolution de problèmes. Par une augmentation progressive du niveau informationnel, plusieurs fonctions opérationnelles sont identifiées pour un AS/RS de produits alimentaires industriels. Ces fonctions utilisent des interpolations statistiques en temps réel pour sélectionner les bacs de stockage et de retrait. Il en résulte que la réaction du AS/RS est de s'adapter aux perturbations stochastiques dans les conditions du système. Des évaluations expérimentales utilisant la technique de l'Analyse à Variance Multiple et des simulations détaillées ont montré que l'approche dynamique proposée est supérieure à la méthode de contrôle industriel courante utilisée dans les systèmes industriels caractérisés par des arrivages (et retraits) en fournées des modèles de demande non-stationnaires et des UL. Ces évaluations suggèrent également qu'une meilleure performance est réalisée avec l'augmentation du niveau informationnel. Le plan de contrôle opérationnel développé dans cet article semble être une excellente alternative de contrôle pour les AS/RS à chargement par unité. Cela est dû à ses besoins limités en calculs et à la productivité augmentée, comme il est démontré ici pour une étude de cas réel.

Eine neue informationstechnische Methode zur betrieblichen Steuerung von automatischen Ein- und Auslagerungssystemen (EL/AL) wird entwickelt und untersucht. Diese Methode basiert auf einem Zustand-Operator-Grundgerüst für Problemlösungen, das sich Künstlicher Intelligenz bedient. Durch ein allmähliches Anheben des Informationsniveaus werden mehrere betriebliche Zielfunk-

tionen ermittelt, die für ein industrielles, palettisiertes Nahrungsmittelprodukt-EL/AL-System wesentlich sind. Diese Funktionen machen zur Anwahl der gewünschten Ein- und Auslagerungsbehälter von statistischen Echtzeit-Interpolationen Gebrauch. Infolgedessen paßt sich das EL/AL-Verhalten automatisch den stochastischen Störeinflüssen der Systembedingungen an. Experimentelle Bewertungen mit Hilfe der vielfachen Varianzanalysentechnik und umfangreicher Simulationen haben gezeigt, daß die vorgeschlagene dynamische Methode dem üblichen industriellen Überwachungsverfahren überlegen ist, das derzeit in Industrieunternehmen gebräuchlich ist, die durch eine schubweise Ankunft (und Auslagerung) der Ladeeinheiten und einer nichtstationären Nachfrage gekennzeichnet sind. Diese Bewertungen deuten ferner darauf hin, daß not zunehmendem Informationsniveau die Leistung des Systems ansteigt. Das betriebliche Steuersystem, das in dieser Abhandlung entwickelt wurde, scheint eine ausgezeichnete Steuerungs-Alternative für Einheitslasten-EL/AL-Systeme zu bieten. Der Grund dafür liegt zum einen in den begrenzten Rechenanforderungen und zum anderen in der verstärkten Produktivität, die hier in einer echten Fallstudie nachgewiesen wurden.