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Minimizing production costs for a robotic assembly system

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Abstract

The objective of this study is to minimize the expected present worth of the production costs incurred over the operational life of a robotic assembly system that is integrated with an Automatic Storage/Retrieval System (AS/RS). Production costs include inventory cost and capital cost of equipment. Inventory cost consists of ordering, holding, and lost-production costs; and all of these costs depend on the scheduling policy for the assembly robots as well as the inventory policy for the AS/RS. Capital cost of equipment depends on the number of depalletizer robots and the number of assembly robots. To identify the minimum-cost design for a certain automotive assembly operation from a given set of alternative system configurations, we present a simulation experiment in which independent replications of each alternative are controlled by a statistical ranking-and-selection procedure that has been adapted to simulation.

1. Introduction

In the past several years, many companies have invested large amounts of capital to implement Automatic Storage/Retrieval Systems (AS/RSs). An AS/RS is defined as "a combination of equipment and controls which handles, stores, and retrieves materials with precision, accuracy, and speed under a defined degree of automation" [1]. Such systems range from simple manually controlled order-picking machines operating in small storage structures to complex computer-controlled storage/retrieval systems that are totally integrated into the manufacturing and distribution process [2]. The main purpose of an AS/RS is to centralize the storage and retrieval operations and thus to increase the efficiency of these operations. In this study we concentrate on AS/RSs that are integrated into the manufacturing process.

Integration of storage, retrieval, and production operations requires a direct linkage between the inventory control policy of the AS/RS and the scheduling policy of the manufacturing system. This linkage accentuates the need for an effective inventory control policy that prevents stockouts at the AS/RS and thus ensures uninterrupted production while simultaneously maintaining an acceptably low level of inventory. In this paper we present a simulation-based method for identifying minimum cost inventory-control and production-scheduling policies in such an integrated manufacturing system. A key feature of this approach is the use of a statistical ranking-and-selection procedure that has been adapted to simulation experiments. Thus in the comparison of alternative operating policies, we can determine the appropriate number of independent replications for each individual policy by taking into account (a) a user-specified threshold on practically significant differences in the average response between policies, and (b) possible disparities among the response variances for different policies. Note that statistical techniques based on classical analysis of variance (ANOVA) cannot easily handle these items.

This paper is organized as follows. Section 2 contains a description of a particular automotive assembly operation to which our methodology is applied. In Section 3 we formulate the general cost function for such an assembly system. Section 4 details the design of a large-scale simulation experiment for this system, including (a) the operating policies to be compared, (b) the simulation model used to implement those policies, and (c) the statistical procedure used to control the execution of each policy and to compare the resulting outputs. The analysis of the experimental results is presented in Section 5. We summarize our conclusions in Section 6. Although this paper is based on Dessouky [3], some of our results were originally presented in Caruso and Dessouky [4].

2. System description

To illustrate our methodology for determining optimal inventory-control and production-scheduling policies, we examine an instrument-panel assembly operation that has recently been implemented at a large automotive production facility in the midwestern United States. As shown in Fig. 1, this system contains δ depalletizer robots, a single AS/RS, and α assembly robots, where δ and α are decision variables to be determined. There are $M=8$ product types that are assembled by the robots, and each product type contains from 2 to 16 subassembly components. There are $C=99$ different types of subassembly components in the system, and the AS/RS can store up to 20,000 subassembly components.

The daily demand for final assemblies has a Poisson distribution with a mean of 5,500. Half of the final-assembly types account for 80% of the daily demand. Specifically, final assemblies of types 1–4 each make up 20% of the total daily demand on the average, while final assemblies of types 5–8 each make up 5% of the total daily demand on the average. Thus the daily demands for final assemblies 1–4 are modelled as independent Poisson random variables each with a mean of 1,100; and the daily demands for final assemblies 5–8 are modelled as independent Poisson random variables each with a mean of 275.

The system depicted in Fig. 1 operates as follows. Subassembly components are ordered from the warehouse in pallets. The travel time from the

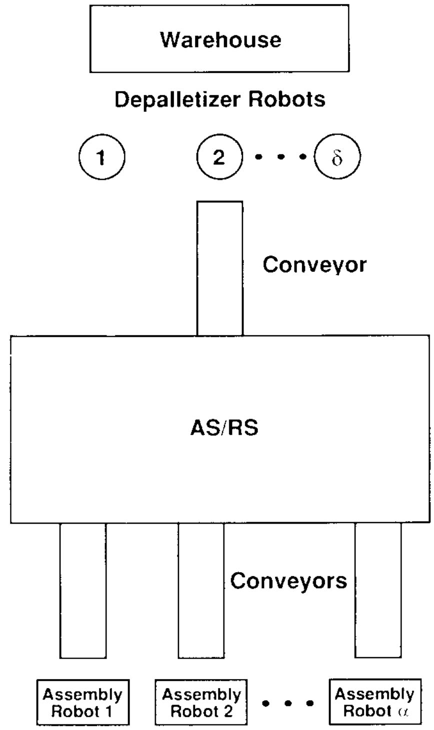

Fig. 1. Layout of the robotic assembly system.

warehouse to the depalletizer robots is 7 minutes. When a pallet arrives at the depalletizer robots, the subassembly components are transferred from the pallet to the conveyor by one of the depalletizer robots at a rate of 1.5 seconds per subassembly. Each subassembly component then travels on the conveyor to a cell of the AS/RS in which it is stored until that component is requested by a robot assembly cell. Including the time to load the subassembly component into a cell of the AS/RS, total travel time on the conveyor is 3 minutes.

The system operates three 8-hour shifts per day, and there are 250 manufacturing days per year. At the beginning of each day, the build schedule for each assembly robot is determined according to the scheduling policy in effect. An assembly cycle for a new unit of the current product type begins with the transfer of all required subassembly components from the AS/RS to the robot assembly cell. Each assembly cycle time is uniformly distributed between 0.65 minutes and 0.75 minutes so that the mean assembly cycle time is $\mu_A=0.70$ minutes for all types of final assemblies. A 10-minute delay is required to change over an assembly robot to production of a different type of final assembly. If an assembly robot finishes its daily build schedule early, then that robot remains idle for the rest of the day. The other possibility is that an assembly robot may fail to complete its build schedule before the end of the day.

Since the daily demand for final assemblies is random, there is a nonzero probability that a day's demand cannot be satisfied. This probability is a complicated function of the following factors: (a) the system's maximum production capacity (that is, the maximum throughput rate of the assembly and depalletizer robots); (b) the number of changeovers and the associated delays that are required each day for each of the assembly robots; and (c) the inventory levels in the AS/RS for the required subassembly components. A lower bound for the probability of unsatisfied demand occurring on any given day is the probability that the daily demand exceeds the maximum daily production rate $1440\alpha/\mu_A$ for the assembly robot(s). If backlogged demands were allowed in this situation, then excessive slippage in the production schedule could occur on days that most or all of the production capacity must be devoted to eliminating the accumulated backlog. To avoid such slippage, we do not allow backlogging; instead a lost-production cost is charged for each unit of unsatisfied demand that occurs during the day.

An inventory review for the AS/RS occurs after every delivery of a subassembly component to a robot assembly cell. When the inventory level of a subassembly component in the AS/RS falls below the reorder point, a replenishment order is sent to the warehouse. The average lead time to fill a replenishment order is $\lambda=45$ minutes; and this includes pallet-loading time at the warehouse, travel time to the AS/RS, and waiting time at the depalletizer robots. The inventory left in the AS/RS at the end of the day is carried over to the next day.

The specific cost components in this system are given below.

(1) The holding cost is \$0.35 per component per day for each type of subassembly.
(2) The ordering cost is \$5.00 per order for each type of subassembly.
(3) The lost-production cost is \$5.00 per unit for each type of final assembly.
(4) The capital cost of a depalletizer robot is \$750,000.
(5) The capital cost of an assembly robot is \$750,000.
(6) The rate of return for the organization is 15% per year.

3. General problem formulation

The cost structure described in this section is a generalization of the costs associated with the specific robotic assembly system described in Section 2. In general the assembly system under consideration produces a set of M final products $\{A_j: j=1,...,M\}$ with respective daily demands $\{D_j: j=1,...,M\}$. The subassembly requirements of the jth assembly are summarized in the vector $\boldsymbol{B}_j \equiv [B_{j1},...,B_{jC}]$, where B_{jc} is the number of units of subassembly c required to produce one unit of assembly j ($j=1,...,M$; $c=1,...,C$). The controllable factors in the production process are enumerated below.

(1) The order of manufacturing final products by the kth assembly robot is summarized in the vector $\boldsymbol{\Omega}_k \equiv [\Omega_{k1},...,\Omega_{kM}]$, where the assignment $\Omega_{ku}=j$ means that product type j is the uth product type to be manufactured by robot k in satisfying the daily demand ($k=1,...,\alpha$; $u, j=1,...,$M). Thus the $\alpha \times M$ matrix

$$\boldsymbol{\Omega} \equiv \begin{bmatrix} \boldsymbol{\Omega}_1 \\ \vdots \\ \boldsymbol{\Omega}_\alpha \end{bmatrix}$$

represents the overall build schedule for a day as determined by the production-scheduling policy in effect.

(2) The inventory policy for stocking subassembly c ($c=1,...,C$) is represented by the reorder point R_c and the order quantity Q_c. The overall inventory policy is summarized by the associated vectors $\boldsymbol{R} \equiv [R_1,...,R_C]$ and $\boldsymbol{Q} \equiv [Q_1,...,Q_C]$.

(3) The number of depalletizer assembly robots is symbolized by δ.

(4) The number of assembly robots is symbolized by α.

The problem is to determine $\boldsymbol{\Omega}$, $\boldsymbol{R}$, $\boldsymbol{Q}$, δ, and α to minimize the expected present worth of the total production cost incurred over the operational life of the system.

The total production cost associated with such a robotic assembly system includes inventory cost and capital cost of equipment. The inventory cost depends on the time-averaged inventory level, the number of replenishment orders placed, and the loss of production due to part unavailability or changeover delays. The capital cost of equipment is determined by the number of depalletizer robots and the number of assembly robots. The present worth of the total production cost can be expressed formally as:

$$\mathrm{PW}=\sum_{t=1}^{T}(1+i)^{-t}\left[\sum_{c=1}^{C}(H_cI_{ct}+K_cJ_{ct})+\sum_{j=1}^{M}p_jL_{jt}\right]+\delta Y+\alpha Z \qquad (1)$$

where

PW = Present worth of total production cost incurred over the planning horizon,
T = Number of time periods (years) in the planning horizon,
i = The organization's rate of return per time period,
H_c = Holding cost per item per time period for subassembly c,
I_{ct} = Time-averaged inventory level over time period t for subassembly c,
K_c = Ordering cost per replenishment order for subassembly c,
J_{ct} = Number of replenishment orders for subassembly c placed during time period t,
p_j = Lost-production cost per item for final assembly j,
L_{jt} = Total lost production for final assembly j during time period t,
Y = Capital cost of a depalletizer robot, and
Z = Capital cost of an assembly robot.

Several remarks should be made about the formulation (1) of the present worth of the production costs. The subexpression $\delta Y+\alpha Z$ represents the expected present worth of the investment in robots, and this includes operating and maintenance costs as well as the salvage value of the robots. Note that PW must be treated as a random variable because production requirements per time period, lead times for replenishment orders, and successive assembly cycle times exhibit substantial random variation. Thus the main objective of this study is to minimize $\mathrm{E}[\mathrm{PW}(\boldsymbol{\Omega}, \boldsymbol{R}, \boldsymbol{Q}, \delta, \alpha)]$ over a prespecified set of values for the decision variables δ and α and over selected policies for setting the matrices $\boldsymbol{\Omega}$, $\boldsymbol{R}$, and $\boldsymbol{Q}$. During the time period t we accumulate the random vectors $\boldsymbol{I}_t\equiv[I_{1t},...,I_{Ct}]$, $\boldsymbol{J}_t\equiv[J_{1t},...,J_{Ct}]$, and $\boldsymbol{L}_t\equiv[L_{1t},...,L_{Mt}]$ respectively representing the inventory levels, ordering levels, and lost-production levels for that period. We assume that the system is in steady-state operation so that the stochastic process $\{[\boldsymbol{I}_t,\boldsymbol{J}_t,\boldsymbol{L}_t]: t=1,...,T\}$ is covariance stationary and the expected periodic cost EPC of operating the system for one time period (exclusive of the cost of robots) is given by

$$\mathrm{EPC}=\sum_{c=1}^{C}(H_c\mathrm{E}[I_{ct}]+K_c\mathrm{E}[J_{ct}])+\sum_{j=1}^{M}p_j\mathrm{E}[L_{jt}], \qquad t=1,...,T \qquad (2)$$

Taking expectations in (1) and substituting (2) into the resulting expression, we obtain a computational formula for the objective function to be minimized

$$\mathrm{E}[\mathrm{PW}]=\left[\frac{(1+i)^T-1}{i(1+i)^T}\right]\mathrm{EPC}+\delta Y+\alpha Z \qquad (3)$$

Thus EPC is the only component of the objective function (3) that must be estimated by simulation, and this observation substantially reduces the amount of simulated experimentation that must be performed to identify the optimal inventory-control and production-scheduling policies.

4. Design of the simulation experiment

In this section we describe the alternative operating policies (scenarios) to be compared, the simulation model used to implement those policies, and the statistical procedure used to compare those policies.

4.1 Alternative scenarios

Within the scope of the application detailed in Section 2, we identified three relevant settings for each of the four controllable factors. Thus, we specified 81 alternative operating policies or scenarios to be compared in determining the minimum cost design for the robotic assembly system.

The number of assembly robots ranges from 3 to 5. At least 3 assembly robots are required to satisfy the expected daily demand. On the other hand, there is only enough physical space to accommodate 5 assembly robots.

The number of depalletizer robots ranges from 1 to 3. Of course at least 1 depalletizer robot is required, and the system has enough physical space for up to 3 depalletizer robots.

To assign the robot build schedule $\boldsymbol{\Omega}$ at the beginning of each working day, we selected 3 alternative scheduling policies for study. The operation of each of these policies is explained below.

- $\mathrm{SPT}_{\mathrm{PBS}}$: Each time an assembly robot finishes production on the current type of final assembly, that robot is assigned to the remaining final-assembly type with the *S*hortest total *P*rocessing *T*ime. Each robot maintains its own individual build schedule. Throughout this paper, the subscript PBS will be used to denote a scheduling policy with *P*arallel *B*uild *S*chedules for each of the assembly robots.
- $\mathrm{LPT}_{\mathrm{PBS}}$: Each time an assembly robot finishes production on the current type of assembly, that robot is assigned to the remaining final-assembly type with the *L*ongest total *P*rocessing *T*ime. Each robot maintains its own individual build schedule.
- $\mathrm{SPT}_{\mathrm{SBS}}$: All of the assembly robots work from a single daily build schedule so that when all α assembly robots have finished production on the current type of final assembly, these robots are assigned as a group to the remaining final-assembly type with the *S*hortest total *P*rocessing *T*ime. Throughout this paper, the subscript SBS will be used to denote a scheduling policy based on a *S*ingle *B*uild *S*chedule for all of the assembly robots.

Some remarks should be made about the selected scheduling policies. In the automotive assembly system, we observe that (a) all types of final assemblies have the same mean robot cycle time μ_{A}; and (b) given the current daily demand D_j for the jth type of final assembly, the conditional expected processing time for that type of final assembly is equal to $D_j\mu_{\mathrm{A}}$. Observations (a) and (b) imply that in the automotive assembly system, the scheduling policy $\mathrm{SPT}_{\mathrm{PBS}}$ (respectively, $\mathrm{LPT}_{\mathrm{PBS}}$) always selects for production the remaining final-assembly type with the smallest (respectively, largest) current daily demand. The policy $\mathrm{SPT}_{\mathrm{PBS}}$ minimizes the sum of completion times of jobs on a single machine and is a good heuristic for parallel identical machines [5]. On the other hand, the policy $\mathrm{LPT}_{\mathrm{PBS}}$ is a good heuristic for minimizing the makespan on parallel identical machines [6].

We examined three alternative inventory policies for assigning the reorder point and order quantity of each subassembly component. All of these policies are variants of the classical lot-sizing technique based on the Economic Order Quantity (EOQ) formula [7]. Although the EOQ formula is derived under the assumption of a nonrandom, continuous, independent demand for a single-level end-item and although the demand for each subassembly component is clearly random, discrete, and dependent, there is substantial evidence that lot-sizing techniques based on the EOQ formula possess the following advantages: (a) these techniques can be effective in production systems subject to uncertainty or random variation in demand [8]; and (b) these techniques are accepted and used in practice [9]. The operation of each of the inventory policies used in this work is explained below.

- $\mathrm{EOQ}_{\mathrm{FRP}}$: Calculate the order quantity Q_c for subassembly c according to EOQ formula

$$Q_c=\left(\frac{2K_c}{H_c}\sum_{j=1}^{M} B_{jc}\mathrm{E}[D_j]\right)^{1/2}, \qquad c=1,\dots,C; \tag{4}$$

and set the reorder point R_c equal to the expected demand during the lead time λ (in days) required to fill an order from the warehouse

$$R_c=\lambda\sum_{j=1}^{M} B_{jc}\mathrm{E}[D_j], \qquad c=1,\dots,C. \tag{5}$$

Throughout this paper, the subscript FRP will be used to denote an inventory policy based on a *F*ixed *R*eorder *P*oint given by (5).

• EOQ_{PRP}: Calculate the order quantity Q_c for subassembly c according to equation (4), compute a mean reorder point μ_{Rc} based on the mean assembly cycle time μ_A for each robot

$$\mu_{Rc} = \alpha\lambda/\mu_A, \qquad (6)$$

and finally generate the actual reorder point R_c as a random sample from a Poisson distribution with mean μ_{Rc}

$$\Pr\{R_c = r\} = \mu_{Rc}^r \exp(-\mu_{Rc})/r!, \qquad r = 0,1,2,.... \qquad (7)$$

Throughout this paper, the subscript PRP will be used to denote an inventory policy based on a *P*oisson *R*eorder *P*oint.

• EOQ_{GRP}: Calculate the order quantity Q_c for subassembly c according to equation (4), compute the mean reorder point μ_{Rc} according to equation (6), and sample the actual reorder point R_c from a geometric distribution with success probability $1/(1+\mu_{Rc})$:

$$\Pr\{R_c = r\} = \frac{1}{1+\mu_{Rc}}\left(1 - \frac{1}{1+\mu_{Rc}}\right)^r, \quad r = 0,1,2,.... \qquad (8)$$

Throughout this paper, the subscript GRP will be used to denote an inventory policy based on a *G*eometric *R*eorder *P*oint.

The basis for the inventory policies EOQ_{PRP} and EOQ_{GRP} requires some explanation. Equation (6) is a rough approximation to the expected number of units of subassembly c that will be required by the assembly robots during the lead time to receive a replenishment order for that subassembly from the warehouse. Since the right-hand side of (6) is independent of the subassembly index c, all types of subassemblies will have the same mean reorder point. If the actual reorder point for each type of subassembly were always set at the mean reorder point given in (6), then multiple simultaneous orders would occur frequently; and this in turn would produce a "bursty" arrival stream of pallets at the depalletizer robots, with the associated requirement for a large buffer. In a simulation project preceding this study, Caruso and Dessouky [4] demonstrated that extreme congestion at the depalletizer robots can be avoided by randomly sampling the reorder points about the mean value μ_{Rc} each time the inventory policy is invoked.

4.2 Simulation model

The simulation model of the automotive assembly system was developed using the SLAM II simulation language [10]. We selected this modeling vehicle because of its well-documented capability to integrate (a) a process-interaction (network) model graphically representing the flow of subassemblies through the system; (b) discrete-event routines controlling initialization and termination of the simulation experiment associated with each scenario; and (c) discrete-event routines controlling the inventory and the daily production schedules. A flow chart of the overall model logic is shown in Fig. 2. After the SLAM executive routine is invoked, the model is initialized by reading the standard SLAM input file together with an input-parameter file that contains the cost coefficients for the system and the decision variables defining the current scenario.

On each independent replication (run) of the current scenario, the first step of the run-initialization procedure is to determine the bill of materials (BOM) for each type of final assembly. This step involves selecting the subassembly components that belong to each type of final assembly. To determine NS, the total number of subassembly components in the current product type, we take a random sample from the discrete uniform distribution with minimum 2 and maximum 16. To assign the respective subassembly types to each of the NS subassemblies, we take a random sample of size NS from the discrete uniform distribution with minimum 1 and maximum 99. A new bill of materials is created for each product type on each simulation run so that the final conclusions of the study will apply to all possible bills of material.

The second step of the run-initialization procedure is to compute $\boldsymbol{R}$, the vector of reorder points, and $\boldsymbol{Q}$, the vector of order quantities, for all types of subassemblies. These vectors depend on the inventory-control policy specified in the input-parameter file. The final step of the run-initialization procedure is to set the initial inventory level for each subassembly type equal to the

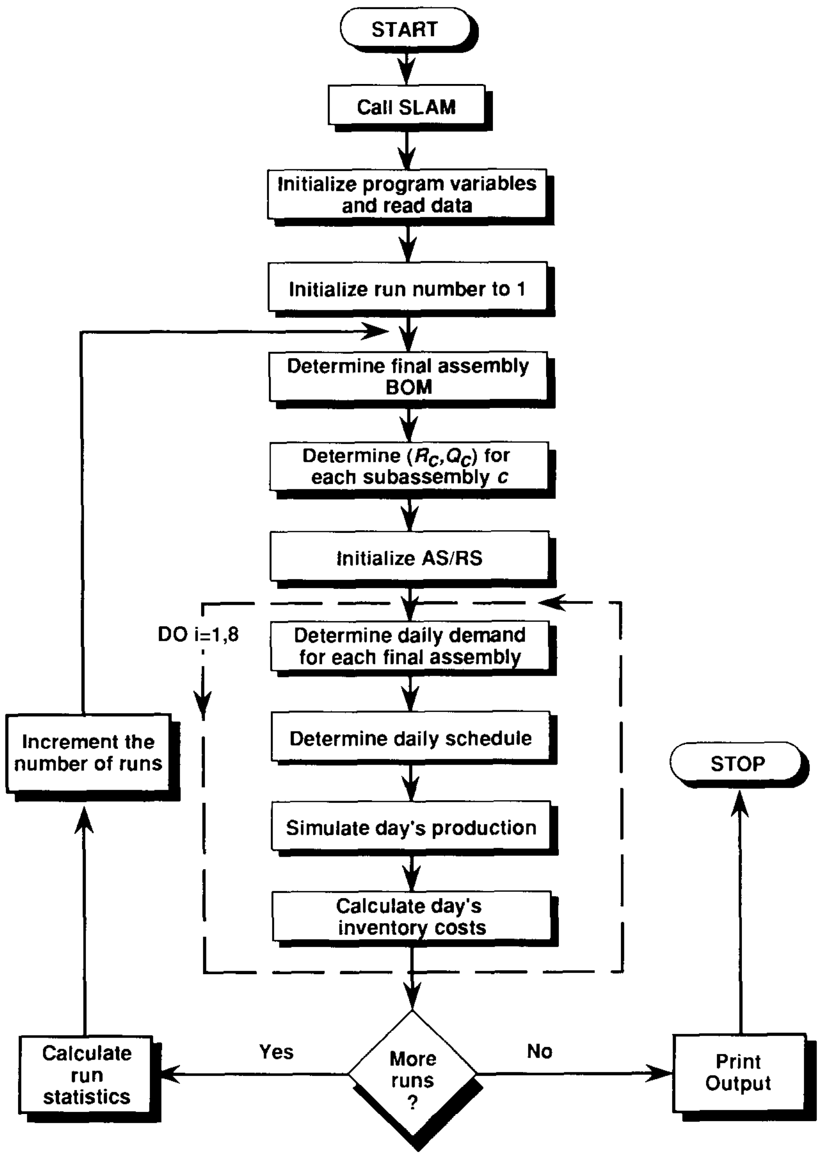

Fig. 2. Flow chart for the simulation of the robotic assembly system.

corresponding order quantity. Note that on each day after the first within each run, the initial inventory level for each subassembly type is simply the ending inventory level for that subassembly type on the previous day.

Each simulation run consists of 10 days of production, where all performance statistics are cleared after a 2-day start-up interval to ensure that the system is in steady-state operation before accumulation of daily inventory costs. To determine the statistics-clearing time, we applied the graphical technique proposed by Welch [11] to three time series that respectively represent the daily holding, ordering, and lost-production costs. At the beginning of each day of production, the daily demand for each final assembly is randomly sampled from the appropriate Poisson distribution as described in Section 2. Moreover, the daily build schedule $\boldsymbol{\Omega}$ for the assembly robots is determined at the beginning of each day using the production-scheduling policy specified in the input-parameter file. The overall statistics on daily inventory costs are updated at the end of each day of simulated operation.

At the end of each 10-day simulation run, the estimated mean daily inventory cost (that is, the sum of the average daily holding, ordering, and lost-production costs) is multiplied by 250 (the number of manufacturing days per year) to yield an estimate of the expected yearly inventory cost (2); then this latter quantity is inserted into the right-hand side of (3) to yield the latest sample estimate of the expected present worth of the total production cost incurred over the 5-year planning horizon. A run-control event is then executed to determine whether (a) the current scenario can be terminated, or (b) additional runs are required. If the current scenario can be terminated, then the final estimator of (3) is computed across all runs in the associated experiment; otherwise the required additional runs are performed before the current scenario is terminated. In the next subsection we describe the statistical-estimation procedure in detail.

4.3 Statistical comparison procedure

To determine the minimum-cost scenario for operating the robotic assembly system, we controlled the runs of each scenario with a statistical ranking-and-selection procedure developed by Dudewicz and Dalal [12]. Let k denote the number of alternative scenarios to be compared so that $k=81$ in our analysis of the automotive assembly system. Moreover, let X_{lu} denote the simulation response (in our case, the present worth of the simulated total production cost) accumulated on the uth run of the lth scenario. We assume that the simulation outputs $\{X_{lu}: u=1,2,...\}$ on successive runs of the lth scenario are normally distributed with unknown mean μ_{Xl} and unknown variance σ^2_{Xl}. Thus for the lth alternative design of the automotive assembly system, we have $\mu_{Xl}=\mathrm{E}[\mathrm{PW}_l]$, where $l=1,2,...,k$.

There are three principal advantages in using the Dudewicz–Dalal procedure for selecting the optimal scenario: (a) in contrast to conventional ANOVA-based techniques for comparing alternative scenarios, the Dudewicz–Dalal procedure does not require equality of the response variances $\{\sigma^2_{Xl}: l=1,...,k\}$ for all alternatives; (b) Sullivan and Wilson [13] have shown that the Dudewicz–Dalal procedure and related ranking-and-selection techniques are robust against many commonly occurring departures from normality; and thus the assumption of normally distributed responses is not restrictive in most practical applications; and (c) the Dudewicz–Dalal procedure allows the user to prespecify a probability P^* and a minimal practically significant difference d^* such that with probability at least P^*, the expected response of the selected scenario will lie less than the distance d^* from the minimum expected response taken across all k alternatives under consideration. Thus, in the analysis of the automotive assembly system, this comparison procedure protects the user against picking a scenario whose expected present-worth total production cost exceeds the minimum of such expected costs by a practically significant dollar amount.

The Dudewicz–Dalal procedure involves two stages of independently replicating each of the k scenarios to be compared. In the first stage of simulating the lth scenario, a user-specified number of runs n_0 must be performed; then the resulting sample variance estimate is used to determine how many additional runs of that scenario are needed in the second stage of the procedure. Note that there is no need to synchronize or coordinate the runs performed on different scenarios. For the lth scenario, the first-stage sample mean and variance are respectively given by

$$\bar{X}_l = \frac{1}{n_0} \sum_{u=1}^{n_0} X_{lu} \tag{9}$$

and

$$S_l^2 = \frac{1}{n_0 - 1} \sum_{u=1}^{n_0} (X_{lu} - \bar{X}_l)^2. \tag{10}$$

The total sample size N_l for scenario l is then computed as

$$N_l = \max\left\{ n_0 + 1, \left\lceil \frac{h_1^2 S_l^2}{(d^*)^2} \right\rceil \right\}, \tag{11}$$

where the notation $\lceil z \rceil$ denotes the smallest integer greater than or equal to z, and h_1 is a constant that depends on k, P^* and n_0. (Selected values of h_1 are given in Table 9.7 on page 329 of Law and

Kelton [14], and a FORTRAN 77 program for computing h_1 is available from the authors on request.)

In the second stage of simulating the lth scenario, we perform $N_l - n_0$ additional runs to obtain the second-stage sample mean

$$\bar{X}'_l = \frac{1}{N_l - n_0} \sum_{u=n_0+1}^{N_l} X_{lu}. \qquad (12)$$

Weighting factors for the sample means of the two stages are respectively defined by

$$W_l = \frac{n_0}{N_l}\left\{1 + \left[\left(\frac{N_l}{h_1^2 S_l^2/(d^*)^2} - 1\right)\left(\frac{N_l}{n_0} - 1\right)\right]^{1/2}\right\}$$

and

$$W'_l = 1 - W_l \qquad (13)$$

so that the final weighted-average estimator of μ_{Xl} is

$$\tilde{X}_l = W_l \bar{X}_l + W'_l \bar{X}'_l \qquad (14)$$

for $l = 1,...,k$. We select the scenario yielding $\min\{\tilde{X}_l : l = 1,...,k\}$, the smallest weighted-average response.

In the analysis of the automotive assembly system, we took $P^* = 0.95$ and $d^* = \$750{,}000$. These parameter values ensure that with probability *at least equal to* 95%, the expected present worth of the total production cost for the selected scenario will differ from the corresponding cost of the optimal scenario by less than the cost of a single robot. In view of the recommendation of Law and Kelton [14] that n_0 should be greater than or equal to 15, we took $n_0 = 25$ in the experiments discussed in the next section.

5. Analysis of experimental results

Table 1 summarizes the notation for the factor levels that were used in all of the simulation experiments on the automotive assembly system. Applying the Dudewicz–Dalal procedure to all of the alternative system configurations defined by Table 1, we concluded that the minimum expected present-worth total production cost is about \$6,700,000; and this is achieved with scheduling policy LPT_{PBS}, inventory-control policy EOQ_{FRP}, $\alpha = 3$ assembly robots, and $\delta = 2$ depalletizer robots. This amount is about \$400,000 less than the expected present-worth total production cost for the second-best scenario and about \$7,000,000 less than that of the worst scenario. Throughout the following discussion, the term *estimated mean cost* refers to a weighted average of the form (14) that is used to estimate either a component of the expected daily inventory cost or the expected present-worth total production cost (3).

TABLE 1

Factor levels used in the simulation experiments

Factor	Notation	Level		
		1	2	3
Scheduling policy	SP	SPT_{PBS}	LPT_{PBS}	SPT_{SBS}
Inventory policy	IP	EOQ_{FRP}	EOQ_{PRP}	EOQ_{GRP}
Number of assembly robots	α	3	4	5
Number of depalletizer robots	δ	1	2	3

The results of the simulation experiments clearly reveal the trade-off between expected present-worth inventory cost and capital cost of robots. The best scenario has a rank of 14 based solely on the estimated mean present-worth inventory cost. The second-best scenario is defined by the factor levels SP = 1, IP = 1, $\alpha = 4$, and $\delta = 2$; and this configuration has the smallest estimated mean present-worth inventory cost. In comparison to the best scenario, the second-best scenario requires one additional assembly robot and uses the SPT_{PBS} scheduling rule, which yields savings of about \$350,000 in expected present-worth inventory cost while incurring an additional present-worth equipment cost of \$750,000.

Table 2 shows the effects of the individual factors on the expected daily holding cost incurred by the AS/RS. Although the single-resource scheduling rule SPT_{SBS} yields the highest estimated mean daily holding cost, the differences in estimated mean daily holding cost between the three scheduling policies do not appear to be practically significant. With regard to inventory-control policies, the EOQ_{FRP} policy yields the smallest estimated mean daily holding cost because the reorder points for this policy are lowest on the average. As a consequence, the AS/RS is

TABLE 2

Effects of individual factors on expected daily holding cost ($)

Factor	Level			Average over all levels
	1	2	3	
SP	2,016	2,011	2,107	2,045
IP	1,725	2,319	2,090	2,045
α	2,068	2,039	2,027	2,045
δ	1,975	2,072	2,088	2,045

TABLE 3

Effects of individual factors on expected daily ordering cost ($)

Factor	Level			Average over all levels
	1	2	3	
SP	1,375	1,369	1,220	1,321
IP	1,319	1,365	1,280	1,321
α	1,276	1,340	1,349	1,321
δ	1,260	1,346	1,359	1,321

generally replenished with subassemblies at later times under the EOQ_{FRP} policy; and this results in lower average inventory levels than are obtained with the EOQ_{PRP} and EOQ_{GRP} policies. Table 2 also shows that as the number of assembly robots increases, the estimated mean daily holding cost decreases. This effect occurs because parts are drawn faster from the AS/RS when more assembly robots are working. Moreover, as the number of depalletizer robots increases, the estimated mean daily holding cost increases because replenishment orders are delivered to the cells of the AS/RS faster in this situation. Nevertheless, it appears that neither the number of assembly robots nor the number of depalletizer robots has a significant impact on the expected daily holding cost incurred by the AS/RS.

Table 3 shows the effects of the individual factors on the expected daily ordering cost, and Table 4 shows the corresponding effects on the expected daily lost-production cost. These tables reveal that the effects of each factor on these two costs are inversely related. This is partially explained by an inverse relationship that generally

TABLE 4

Effects of individual factors on expected daily lost-production cost ($)

Factor	Level			Average over all levels
	1	2	3	
SP	894	670	4,123	1,896
IP	1,989	1,013	2,685	1,896
α	2,853	1,576	1,258	1,896
δ	3,308	1,303	1,076	1,896

holds between the number of replenishment orders placed and the quantity of unsatisfied demand. For example, the single-resource scheduling policy SPT_{SBS} has the lowest estimated mean daily ordering cost but the highest estimated mean daily lost-production cost. Under the SPT_{SBS} policy, all of the assembly robots simultaneously produce the same type of final assembly; and thus all of the assembly robots tend to require the same types of subassembly components from the AS/RS at the same times. The resulting inventory shortages tend to interrupt production more often during the day so that the later entries in the daily build schedule – that is, the production plans for the final assemblies with the highest daily demands – tend to go unfinished more often; and the net effect is that under the SPT_{SBS} rule, an increase in lost production for high-demand products is accompanied by a reduced number of replenishment orders for the associated subassembly components. A similar analysis shows that the LPT_{PBS} rule yields a smaller estimated mean daily lost-production cost than the SPT_{PBS} rule because LPT_{PBS} tends to minimize the makespan (that is, the completion time) of the build schedule for each robot; and since final assemblies with the largest daily demand are produced first, the LPT_{PBS} rule tends to maximize the number of final assemblies produced each day and minimize the estimated mean daily lost-production cost.

Table 4 also reveals that EOQ_{GRP} is the inventory-control policy with the largest estimated mean daily lost-production cost. Observe that the policies EOQ_{PRP} and EOQ_{GRP} have the same expected value for the reorder point R_c

$$\mu_{Rc} \equiv \mathrm{E}[R_c \mid \mathrm{EOQ_{PRP}}] \\ = \mathrm{E}[R_c \mid \mathrm{EOQ_{GRP}}] \quad (15)$$

By contrast, the relationship between the coefficients of variation of R_c for these two policies is given by

$$\mathrm{CV}[R_c \mid \mathrm{EOQ_{GRP}}] \equiv \frac{\{\mathrm{Var}[R_c \mid \mathrm{EOQ_{GRP}}]\}^{1/2}}{\mathrm{E}[R_c \mid \mathrm{EOQ_{GRP}}]} \\ = (1+\mu_{Rc}^{-1})^{1/2} > \mu_{Rc}^{-1/2} = \mathrm{CV}[R_c \mid \mathrm{EOQ_{PRP}}] \quad (16)$$

Thus, we conclude that for a given level of the mean reorder point μ_{Rc}, increasing the variability of the reorder point (that is, increasing the coefficient of variation for R_c) generally causes more lost production to occur. Wemmerlöv [8] observed similar effects by increasing the variability of the demand process for a given level of the mean demand per time period. On the other hand, we observe that policy $\mathrm{EOQ_{PRP}}$ has a smaller estimated mean daily lost-production cost than policy $\mathrm{EOQ_{FRP}}$ because in the automotive assembly system, the fixed reorder point (5) for policy $\mathrm{EOQ_{FRP}}$ is smaller than the mean reorder point (6) for policy $\mathrm{EOQ_{PRP}}$; and thus production-stopping shortages occur at the AS/RS more frequently with policy $\mathrm{EOQ_{FRP}}$.

Table 5 summarizes the effects of individual factors on the expected present worth of total inventory cost over the 5-year planning period. The qualitative effects of each factor on the total inventory cost are the same as for the expected daily lost-production cost, indicating that the expected present-worth lost-production cost is the most significant component of the expected present-worth total inventory cost.

Table 6 summarizes the separate effects of each of the factors on the expected present worth of the total production cost incurred over the 5-year planning horizon. For each production-scheduling policy, Table 6 displays the grand mean of the present-worth total production cost averaged over all scenarios using that policy; and similar results are presented for each of the other factors under study. For example, we see that the scheduling policy $\mathrm{LPT_{PBS}}$ yields the lowest grand mean for present-worth total production cost, and this is consistent with the results of the ranking-and-selection procedure. On the other hand, the inventory-control policy $\mathrm{EOQ_{PRP}}$ yields the lowest grand mean for present-worth total production cost; and at first glance this conclusion does not appear to be consistent with the results of the ranking-and-selection procedure.

The estimates in Table 6 can be reconciled with the results of the ranking-and-selection procedure by considering the interactions between the controllable factors in the experiment (see Anderson and McLean [15], pp. 66-71 and pp. 275-277). The minimum-cost scenario identified by the Dudewicz–Dalal procedure uses the inventory-control policy $\mathrm{EOQ_{FRP}}$. Observe that the lowest-cost scenario using inventory policy $\mathrm{EOQ_{PRP}}$ has rank 6, and this scenario is more expensive that the minimum-cost scenario by roughly $530,000. If we based the design of the robotic assembly system solely on the results in Table 6 and we neglected the interaction effects, then we would select scheduling policy $\mathrm{LPT_{PBS}}$, inventory policy $\mathrm{EOQ_{PRP}}$, $\alpha=4$ assembly robots, and $\delta=2$ depalletizer robots. This scenario has a rank of 16 and an estimated mean present-worth total production cost of about $7,700,000.

TABLE 5

Effects of individual factors on expected present worth of total inventory cost ($) over a 5-year planning horizon

Factor	Level 1	Level 2	Level 3	Average over all levels
SP	3,591,644	3,395,131	6,245,430	4,410,735
IP	4,218,858	3,938,291	5,075,056	4,410,735
α	5,194,771	4,152,416	3,885,018	4,410,735
δ	5,483,075	3,956,720	3,792,410	4,410,735

TABLE 6

Effects of individual factors on the expected present worth of total production cost ($) over the 5-year planning horizon

Factor	Level 1	Level 2	Level 3	Average over all levels
SP	8,091,644	7,895,131	10,745,430	8,910,735
IP	8,718,858	8,438,291	9,575,056	8,910,735
α	8,944,771	8,652,416	9,135,018	8,910,735
δ	9,233,075	8,456,720	9,042,410	8,910,735

Therefore, the cost of neglecting the interaction effects would be about $1,000,000.

6. Conclusions

In this paper we have presented a simulation model of an AS/RS feeding a robotic assembly system. The modeling objective was to minimize the expected present worth of total production cost incurred over the operational life of the system. Using a statistical ranking-and-selection procedure that has been adapted to discrete simulation experiments, we identified a minimum-cost system design specifying the production-scheduling policy for the assembly robots, the inventory-control policy for the AS/RS, the number of assembly robots, and the number of depalletizer robots.

Even though this study was performed on a single specific system, the method of analysis detailed in this paper can be applied to any manufacturing system that is integrated with an AS/RS. Moreover, several general conclusions can be drawn from this study. (a) Frequently there exist highly significant interactions between the design factors for such manufacturing systems, and these interactions invalidate simple one-factor-at-a-time procedures for finding the minimum-cost system design. (b) In the analysis of simulation-generated responses (costs), substantial disparities between the response variances for different system configurations invalidate classical ANOVA techniques. We believe that a valid and efficient approach to the problem of selecting optimal system designs can be based on statistically designed simulation experiments using appropriate ranking-and-selection procedures that have been adapted to simulation. To screen a large number of alternatives, we recommend applying the restricted subset selection procedure of Sullivan and Wilson [13] in a pilot study so that all inferior alternatives can be quickly identified and eliminated from further consideration.

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