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USING COMPUTER SIMULATION TO OPTIMIZE FLEXIBLE MANUFACTURING SYSTEM DESIGN

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ABSTRACT

An FMS is a highly integrated manufacturing system. The inter-relationships between its components are not well understood. Consequently, it has not been possible to develop closed form analytic models of FMSs. Computer simulation has been extensively applied to study their performance. The optimal design of FMSs is an important problem. In this research a computer simulation model of an FMS is interfaced with the Hooke-Jeeves algorithm to search an optimum design without full factorial experimentation. Some modifications of the HJ algorithm are needed to accommodate the stochastic nature of computer simulation.

1. INTRODUCTION

The optimal design of flexible manufacturing systems (FMS) is a complex problem. This is because an FMS is a highly integrated manufacturing system and the inter-relationships between its various components are not well understood. Due to this complexity, it has not yet been possible to develop closed form analytic models to accurately determine the level of performance of different designs.

Computer simulation is a widely used numeric modelling technique for the analysis of complex systems such as FMSs (Cheng 1985, Jain & Foley 1986, Kalkunte et. al 1986, Mellichamp & Wahab 1987). However, simulation is an evaluative technique (Suri 1984), i.e. it provides an accurate estimate of performance for a given set of decisions. To search an optimal set of decisions, an evaluative technique must be interfaced with a generative procedure i.e. a procedure that generates alternate sets of decisions. One such generative procedure is the Hooke-Jeeves algorithm.

The Hooke-Jeeves (HJ) algorithm is a search procedure useful for searching the optimum of complex functions. However, for this procedure to work, it must be possible to evaluate the function deterministically. A function represented by a simulation model cannot be evaluated deterministically. Any measure obtained from a simulation experiment is a stochastic variable characterized by some probability distribution. Consequently, the HJ procedure must be modified to allow the stochastic evaluation of the function being optimized.

In this research, a modified version of the HJ procedure is developed. A simulation model representing an FMS is interfaced with the modified version of the HJ procedure. Application of the procedure is demonstrated through an example.

2. NEED FOR MODIFICATION OF HJ ALGORITHM

The HJ algorithm is a widely used search procedure to optimize a function and identify the corresponding levels of the variables that affect it. The method performs two types of search routines cyclically: an exploratory search and a pattern search. The exploratory search is conducted along the individual coordinate directions in the neighborhood of a reference point. The pattern search proceeds along the direction defined by the starting and ending points of the exploratory search.

However, the HJ procedure requires deterministic evaluation of the function being optimized. Here, this function is represented by a simulation model which provides a stochastic estimate for a given set of decisions. Consequently, the HJ procedure will need modification with respect to some of the statistical aspects of simulation.

2.1 Statistical Aspects of Simulation

Estimates of response obtained from a simulation model are random variables. Consequently, the estimate obtained from a single simulation run could vary greatly from the true value of the response. Inferences made using single estimates would have a significant probability of being erroneous. Therefore, several values of the response must be obtained for valid inferences to be possible. However, values of the response obtained from different points of a simulation run are usually not independent. Thus, statistical analyses based on an assumption of independent identically distributed (IID) observations are not directly applicable (Law & Kelton 1982).

The statistical analysis of data obtained from a simulation model differs depending on whether the system is terminating or non-terminating. Terminating systems are those which operate during certain fixed intervals of time. Non-terminating systems are those which do not have any boundaries on the duration or period of operation. An FMS is generally modelled as a non-terminating system.

Non-terminating systems are analyzed on the basis of data collected when the system has achieved steady state. Steady state is achieved when the measures of performance or responses are defined as:

$$F(x) = \lim_{t \to \infty} F_{t,c}(x) \quad \text{for } C(0) = any\, c$$

where

F(x) = steady state value of the measure

$F_{t,c}(x)$ = Transient distribution of the measure given an initial condition C(0) = c.

Steady state does not mean that the response for a single simulation run will become constant after some point in time, but that the distribution of the measure becomes invariant. Consequently, any realization of the measure from a simulation run is an unbiased estimator of the true value of the measure. In the FMS design problem, this measure is productivity (Nandkeolyar 1988).

In the FMS design problem, inferences have to be drawn regarding the superiority of one design over another. In order to make these inferences, it is usually not enough to obtain one unbiased estimate of the true mean but rather to construct a confidence interval for the true mean of the measure.

Several techniques appear in the literature for obtaining the desired confidence intervals based on computer simulation. The method of batch means is the most commonly used procedure. Under this procedure, let

$$\nu = \lim_{m \to \infty} \frac{\sum_{i=1}^{m} Y_i}{m}$$

where,

ν is the steady state average response

Y_i is the i^{th} realization of the response.

Assume that $\{Y_i, i \geq 1\}$ is a covariance stationary process with $E(Y_i) = \nu$ for all i. The simulation run length m is divided into n batches of length d such that m = nd. Now,

$$\overline{Y}_j(d) = \frac{\sum_{i=1}^{d} Y_{ij}}{d}, \quad j = 1, 2, \ldots, n$$

is the batch mean of batch j. And,

$$\overline{Y}(n,d) = \frac{\sum_{j=1}^{n} \overline{Y}_j(d)}{n} = \frac{\sum_{i=1}^{m} Y_i}{m}$$

is the grand mean of the measure.

In order to make valid inferences about the performance of the system, the batch means could be used to construct a confidence interval for the true mean provided:

a. The batch means are IID random variables, and

b. The batch means are not correlated.

Both these conditions can be satisfied if d is large. Further, due to the central limit theorem, which can be invoked if both n and d are large enough, $\overline{Y}_j(d)$ will be IID normal random variables with mean ν. Now an approximate 100(1 - α) percent confidence interval for ν may be written as

$$\overline{Y}(n,d) \pm t_{n-1,(1-\alpha)/2} \frac{s_{\overline{Y}(d)}(n)}{\sqrt{n}}$$

where

$$s^2_{\bar{Y}(d)}(n) = \frac{\sum_{j=1}^{n} [\bar{Y}_j(d) - \bar{Y}(n,d)]^2}{n-1}$$

This estimate of variance of the mean may now be used to draw inferences about the performance of one system compared to the performance of another system. In this case, a hypothesis of the form:

$$H_0: \nu_A = \nu_B$$

$$H_A: \nu_A > \nu_B$$

may be tested where ν_A and ν_B are the true means of the measure for two systems A and B. The appropriate test statistic is

$$t = \frac{\bar{Y}_A(n_A,d) - \bar{Y}_B(n_B,d)}{\sqrt{s_p^2(\frac{1}{n_A} + \frac{1}{n_B})}}$$

where

$$s_p^2 = \frac{(n_A - 1)s^2_{\bar{Y}_A}(n_A) + (n_B - 1)s^2_{\bar{Y}_B}(n_B)}{n_A + n_B - 2}$$

is the pooled variance of the means.

3. MODIFICATION OF THE HJ ALGORITHM

The general algorithm for maximizing an objective function is described by the following steps (Bazarra & Shetty 1979):

1. Start with an arbitrarily chosen point $X_1 = \{x_1, x_2, ..., x_n\}$ called the starting or base point, and prescribed step lengths Δx_i in each of the coordinate directions u_i = 1,2, ...,n. Set k = 1.

2. Compute the value of the objective function $p_k = f(X_k)$. Set i = 1, and the temporary base point $Y_{k,0} = X_k$.

3. The input variable x_i is perturbed about the current temporary base point $Y_{k,i-1}$ to obtain the new temporary base point as

$$Y_{k,i} = \begin{cases} Y_{k,i-1} + \Delta x_i u_i, & if,\ p^+ = f(Y_{k,i-1} + \Delta x_i u_i) > f(Y_{k,i-1}) \\ Y_{k,i-1} - \Delta x_i u_i, & if,\ p^- = f(Y_{k,i-1} - \Delta x_i u_i) > f(Y_{k,i-1}) \\ Y_{k,i-1}, & otherwise \end{cases}$$

Set i = i+1. If i > n go to step 4, otherwise go to step 3.

4. If $Y_{k,n} = X_k$, set $\Delta x_j = \Delta x_j/2$, j = 1, 2, ..., n, go to step 5, otherwise go to step 6.

5. If $\max_j(\Delta x_j) < \epsilon$, go to step 8, otherwise set i = 1, and go to step 3.

6. Set the new base point $X_{k+1} = Y_{k,n}$. Establish a pattern direction $S = X_{k+1} - X_k$ and find a point

$$Y_{k+1,0} = \begin{cases} X_{k+1} + \lambda S, & \text{if } p^\lambda = f(X_{k+1} + \lambda S) > p_{k+1} = f(X_{k+1}) \\ X_{k+1}, & otherwise \end{cases}$$

λ is the step length along the direction of the pattern search.

7. Set k = k+1, $p_k = p(Y_{k0})$, i = 1, go to step 3.

8. Stop.

This procedure may be used to minimize a function by either reversing the direction of the inequalities, or by multiplying the objective function by -1.

The HJ procedure assumes that the value of the objective function can be determined without error for all combinations of input variables. This is not the case in the FMS design problem since the objective function is estimated on the basis of simulation experiments. Due to the stochastic nature of these experiments, the value of productivity is not deterministically known.

3.1 Stochastic Nature of Objective Function

The productivity of a particular FMS design is evaluated by a simulation model. Due to the nature of simulation, the results are stochastic. This means that the value of productivity obtained from the experiments belong to some probability distribution. Using the concepts of blocking, and the central limit theorem, the value of productivity obtained from each block can be assumed to belong to a normal distribution. These results allow the estimation of a mean value of the productivity and standard error of the sample means for a particular design.

The stochastic nature of the evaluation of the objective function causes two problems. Since the function can only be estimated by a probability distribution, improvements in the value of the function can be established only when statistically significant improvements occur. Also, repeated evaluation of the objective function for the same set of input variables can create problems when the objective function is a stochastic variable. The most critical problem is cycling. Cycling can occur if a point previously found to be superior (inferior) is later found to be inferior (superior) to the same reference point. In addition, computing effort to rerun simulations would be wasted. Some modifications to the HJ procedure are warranted to accommodate these problems.

In order to overcome these problems, repeated samples must not be drawn. Instead, a sufficiently large sample size should be chosen to ensure reliable estimates of the mean and standard error. Objective function values obtained for every evaluated configuration must be stored and reused in hypothesis tests.

3.2 The Modified Hooke-Jeeves Algorithm

Three modifications have been made to the HJ algorithm to accommodate the idiosyncrasies of this problem.

a. The procedure for determining an improvement in the response has been modified to accommodate its stochastic nature. Consequently, only statistically significant improvements in the value of the response are recognized, and therefore trigger a shift in the base point. The original algorithm assumes that the response can be evaluated deterministically, so that infinitesimal improvements in its value are recognized.

b. Figure 1 is a plot of productivity as a function of input x_i. Consider the points 1 and 2. The mean values of productivity at these points are $\bar{p}_1$ and $\bar{p}_2$. Now, if

$$\bar{p}_2 - \bar{p}_1 < zs_{\bar{p}}$$

where z is the unit normal variate and $s_{\bar{p}}$ is the standard error of the mean, the direction x_i will not be identified as a direction in which improvements can be achieved. However, consider another point 3. The value of productivity at this point is $\bar{p}_3$. Now, if

$$\bar{p}_3 - \bar{p}_1 > zs_{\bar{p}}$$

this direction x_i will be identified as a direction in which improvements can be achieved. Consequently, in order to improve the capability of the algorithm to identify potential

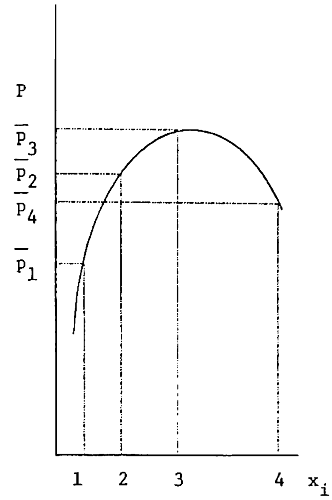

Figure 1: Impact of Step Size on the Hooke-Jeeves Algorithm

directions of improvement, Δx_i must be as large as possible. Large values of Δx_i alone does not solve the problem. Note that at point 4,

$$\bar{p}_4 - \bar{p}_1 < zs_{\bar{p}}$$

The HJ algorithm with modification a alone would not identify x_i as a direction where improvements can be achieved.

This requires the second modification. In the original HJ procedure, each axis is explored for a given step size. If no axis produces a superior point, the step sizes are reduced by a predetermined factor and the exploratory search is conducted again. The reduction in step size is permanent. Here, this procedure is modified. An axis is explored starting a predetermined initial step size. If a superior point is not found, the step size is reduced by a predetermined factor. This procedure is followed until either a superior point is found or the step size reaches a predetermined value ϵ. When either of these occurs, another axis is explored and the step size of the previously explored axis is set back to the initial value.

Large values of initial step size are likely to produce better results, but greatly increase the number of alternate evaluations to be performed. Consequently, initial step size should be chosen with great care.

Figure 2 demonstrates how this modification helps identify directions of improvement which may otherwise have been missed. In this figure,

$$\bar{p}_2 - \bar{p}_1 < z s_{\bar{p}}$$

however,

$$\bar{p}_3 - \bar{p}_1 > z s_{\bar{p}}$$

so that x_i is identified as an improving direction.

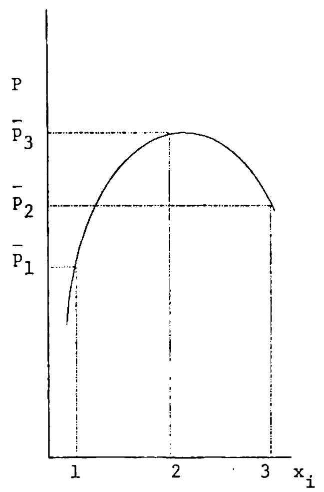

Figure 2: Modification of Hooke-Jeeves Algorithm

c. The stopping criteria for the original algorithm is reached when the step size along all the coordinate axes is reduced to some predetermined finite value ϵ. For the FMS design problem ϵ is specified as zero. In addition, all reference points and step sizes are integers. This is because the decision variables (i.e. number of machines) can only be integer quantities.

The modified HJ algorithm is:

1. Start with an arbitrarily chosen point $X_1 = \{x_1, x_2, ..., x_n\}$ called the starting or base point, and prescribed step lengths Δx_i in each of the coordinate directions u_i = 1,2, ...,n. Set k = 1.

2. Compute the value of the objective function $p_k = f(X_k)$. Set i = 1, and the temporary base point $Y_{k,0} = X_k$.

3. If Δx_i = 0 go to step 4. The input variable x_i is perturbed about the current temporary base point $Y_{k,i-1}$ to obtain the new temporary base point as

$$Y_{k,i} = \begin{cases} Y_{k,i-1} + \Delta x_i u_i, \ if, \ p^+ = f(Y_{k,i-1} + \Delta x_i u_i) > f(Y_{k,i-1}) + z s_{\bar{p}} \\ Y_{k,i-1} - \Delta x_i u_i, \ if, \ p^- = f(Y_{k,i-1} - \Delta x_i u_i) > f(Y_{k,i-1}) + z s_{\bar{p}} \\ Y_{k,i-1}, \quad otherwise \end{cases}$$

If $Y_{k,i} = Y_{k,i-1}$ set $\Delta x_i = INT(\Delta x_i/2)$ and go to step 3, otherwise go to step 4.

4. Reinitialize Δx_i. Set i = i+1. If i > n go to step 5, otherwise go to step 3.

5. Set the new base point $X_{k+1} = Y_{k,n}$. Establish a pattern direction $S = X_{k+1} - X_k$. If S=0 go to step 7 otherwise find a point

$$Y_{k+1,0} = \begin{cases} X_{k+1} + \lambda S, \ \text{if } p^\lambda = f(X_{k+1} + \lambda S) > p_{k+1} = f(X_{k+1}) \\ X_{k+1}, \quad otherwise \end{cases}$$

λ is the step length along the direction of the pattern search.

6. Set k = k+1, $f_k = f(Y_{k,0})$, i = 1, go to step 3.

7. Stop.

These modifications essentially require that the null hypotheses in the appropriate one tailed hypothesis tests of the form:

$$H_O: \bar{p}^{+(-)} = \bar{p}_{k,i-1}$$
$$H_A: \bar{p}^{+(-)} > \bar{p}_{k,i-1}$$

or,

$$H_O: \bar{p}^\lambda = \bar{p}_{k+1}$$
$$H_A: \bar{p}^\lambda > \bar{p}_{k+1}$$

be rejected in favor of the alternate hypothesis for a prescribed level of confidence. The standard error for these hypothesis tests are computed as the pooled standard errors respectively as follows:

$$s_{\bar{p}}^2 = \frac{\sum^{n_1}[p_{k,i-1} - \bar{p}_{k,i-1}]^2 + \sum^{n_2}[p^{+(-)} - \bar{p}^{+(-)}]^2}{n_1 + n_2 - 2} \times \left[\frac{1}{n_1} + \frac{1}{n_2}\right]$$

or

$$s_{\bar{p}}^2 = \frac{\sum^{n_1}[p^\lambda - \bar{p}^\lambda]^2 + \sum^{n_2}[p_{k+1} - \bar{p}_{k+1}]^2}{n_1 + n_2 - 2} \times \left[\frac{1}{n_1} + \frac{1}{n_2}\right]$$

Here n_1 and n_2 are the sample sizes used to estimate the mean value of the objective function at the points considered in the hypotheses being tested. Usually, equal sample sizes are taken.

3.3 Effect of the Modifications

The modifications made to the HJ algorithm are mainly procedural and do not violate any of the major assumptions of the original work. However, there are some questions regarding the statistical aspects of the large number of hypothesis tests that are conducted in a sequential manner. Note that each hypothesis test of the nature

$$H_0: \mu_i = \mu_j$$

$$H_A: \mu_i > \mu_j$$

involves a risk of making a erroneous decision.

Type I error, rejecting a null hypothesis when in fact it is true, is committed with a probability α. If the hypotheses were independent, as the number of hypotheses tested increases, the type I error cumulates according to $1-(1-\alpha)^n$, where n is the number of hypotheses tested. However, this is not the case here. Each hypothesis test is a one-tailed test in which the base point is based on the result of the previous hypothesis test.

For example if the i^{th} hypothesis is

$$H_0: \mu_1 = \mu_0$$

$$H_A: \mu_1 > \mu_0$$

and the null hypothesis is rejected, then the $i+1^{st}$ hypothesis is

$$H_0: \mu_2 = \mu_1$$

$$H_A: \mu_2 > \mu_1$$

If this null hypothesis is also rejected, then the type I error made in rejecting the null in the following hypothesis is less than α.

$$H_0: \mu_2 = \mu_0$$

$$H_A: \mu_2 > \mu_0$$

Hence, due to the interdependence of the sequence of hypotheses being tested, the type I error does not accumulate.

Of greater importance here is type II error, failing to reject the null hypothesis when in fact it is false. If a type II error is committed, a point which is truly a superior point would not be identified. This could seriously impair the progress of the algorithm.

Consequently, it is important to minimize β, the probability of committing a type II error. $1-\beta$ is known as the power of the test, and is to be maximized.

The power of the test is a complex quantity. It depends on the difference between the means that it must be able to identify $(\mu_A - \mu_B)$, the number of data points in the sample means n, the standard deviation of the distribution, the significance level of the test α, and whether a one-tailed or a two-tailed test is being conducted (Snedecor & Cochran, 1980). The power of a test is given by:

$$1-\beta = Prob\left\{Z > Z_{1-\alpha} - \frac{\sqrt{n}(\mu_A - \mu_B)}{\sigma}\right\}$$

Since σ is not known, it is replaced by its estimate s and the normal variate Z is replaced by t with the appropriate degrees of freedom. Hence,

$$1-\beta = Prob\left\{t > t_{\eta,1-\alpha} - \frac{\sqrt{n}(\mu_A - \mu_B)}{s}\right\}$$

It is seen that $(1-\beta)$ can be increased by increasing n, α, $(\mu_A - \mu_B)$ or decreasing s. High values of n would increase costs since more replications would be needed. Large values of α would result in a high rate of type I error. Since $(\mu_A - \mu_B)$ and σ are exogenous to the design problem, only n is under the control of the designer. Hence, power can be increased only by increasing n. This may make the implementation of the procedure uneconomical. In addition, large values of α would also increase power, though this may produce unacceptable levels of type I error.

4. EXAMPLE

The FMS design problem involves the specification of the level of inputs required to produce a set of parts in a way that productivity is maximized.

Here an FMS is modelled using computer simulation. Since simulation is an evaluative technique, this model is interfaced with an optimization routine to search the optimal design.

Table 1: Part Families, Operation Sequence and Processing Time

Part Family	Operation Sequence 1	2	3	4	Mean Processing Time 1	2	3	4
1	1	2	3	4	20	15	35	10
2	3	2	1	4	35	15	20	10
3	1	3	2	4	20	35	15	10

A modified Hooke-Jeeves (HJ) algorithm is used as the search procedure.

4.1 Problem Definition

Consider an FMS that receives orders for parts according to some arrival process. These parts could belong to a single or several part families. Here, parts that undergo the same sequence of operations are assumed to belong to the same part family. Each part family consists of several part types. Though each part type belonging to a part family follows the same route, they are differentiated by the individual processing time for each operation.

The FMS is assumed to contain machines that together can perform all the operations for all the part families under consideration. In order to provide sufficient capacity, several units of each type of machine are installed according to a functional layout.

Each group of similar machines has a limited number of input buffer spaces from which parts are drawn for processing. Upon completion of processing, parts are placed in a limited capacity output buffer. In addition to buffers attached to machine groups, a limited number of buffers are available at a central location where arriving parts are stored before being released to the system.

Automated guided vehicles (AGVs) transport parts from the central buffer to the input buffers of the appropriate machines, and from the output buffers to input buffers or the exit station. Several AGVs may be employed to provide sufficient material handling capacity.

4.2 Problem Parameters

Assume that an FMS is capable of conducting four operations. It is, therefore, capable of processing all parts that require these four operations. Assume also that these parts are grouped into three part families i.e. groups of parts that follow the same route.

Parts that arrive to the system all require four operations to be completed. Three part families are defined. Table 1 shows the sequence of operations for each part family, and the corresponding processing time. Note that operation number 4 is always the last one to be completed, and that each operation requires the same amount of time for all part families. If a machine must process parts from different part families consecutively, a set-up time is incurred.

Within each part family there are several individual parts. These parts follow the same sequence of operations as other members of the part family, but require a different amount of time at each operation. Here, this specific processing time is achieved by multiplying the mean processing time for the part family for an operation by a factor drawn from discrete probability distributions. The mean of these distributions is 1. The discrete probability distributions used for these three part families appear in Table 2. Note that this translates to n^4 parts in each part family, where n is the number of factors defined for a part family. For example, in part family 1, there are 3^4 parts.

Table 2: Probability Distributions of Processing Time Multipliers

Part Family				
1	Factor	0.80	1.00	1.30
	Probability	0.30	0.50	0.20
2	Factor	0.80	0.93	1.20
	Probability	0.10	0.60	0.30
3	Factor	0.80	1.00	1.20
	Probability	0.30	0.40	0.30

Parts are assumed to arrive at the FMS at fixed intervals of 40 time units with a batch size of 5. All parts in a batch belong to the same part family, though they may not be the same part. All part families are represented equally in the set of arriving parts.

Four types of machines are employed in the system - one for each operation. An objective of the design process is to determine the optimum number of machines of each type that must be employed.

Three types of buffers are defined for the FMS. The central buffer stores parts until they can be released to the shop. The input and output buffers are located near machines. Input buffers provide space for parts that must be processed on the corresponding machine. Output buffers store parts that have been processed at the corresponding machine and are awaiting transportation to the next station. Usually a limited number of buffer spaces are available. The FMS design process attempts to determine the optimum number of buffer spaces at each location.

The material handling system is assumed to consist of AGVs. Several units of AGVs may be employed and they travel at a speed that takes them 1 time unit to move from any location to any other location in the FMS. An objective of the FMS design process is to determine the optimum number of AGVs to be employed.

Work in process is another form of input to the system. Though it cannot be directly determined by the designer, it is affected by the design parameters.

4.3 Objective Function

Productivity is the objective function that must be optimized and the settings of the design parameters that result in this optimum level is to be identified.

Productivity is defined as:

$$P = \frac{Q}{\sum_{i=1}^{n} C_i I_i}$$

where,

Q = The number of parts produced by the system

C_i = the cost of input i

I_i = the level of input i

4.4 Modified Hook-Jeeves Procedure

In order to be effective, this search procedure requires the careful selection of some of its parameters. These parameters are the initial step size along the coordinate axes and the pattern direction, the significance level of the hypothesis tests that will be conducted, and the power of the tests in detecting practically significant improvements in productivity.

The initial step size along the coordinate directions is a very critical parameter of the HJ procedure. A large value of the step size will result in the identification of a large number of candidate designs to be evaluated. This could become very costly. While a small value for the step size could result in the evaluation of a fewer number of alternate FMS designs, it may cause the procedure to miss the optimum. Hence, a balance between the amount of computer time used and the risk of stopping at a sub-optimal design must be reached. Intimate knowledge of the specific system could help in establishing a good value for the initial step length.

After some preliminary experimentation, an initial step size of 2 along all coordinate axes was chosen. This is because the stopping point for this step size produced productivity values within 2% of the stopping point when the step size was 4. Three times as many alternate designs were evaluated in the later case. Preliminary exploratory investigations found that a power of approximately 70% is achieved when $n = 10$, $\alpha = .15$, $s = .2$ and $(\mu_A - \mu_B) = .1$.

Recall, the modified HJ procedure requires a high value of power as opposed to a low level of significance to identify superior designs.

4.5 Simulation Model

A simulation model for this problem was developed using SIMAN. This model was directly interfaced with with a FORTRAN program of the modified Hooke-Jeeves procedure.

The initial set of decision variable i.e. the number of machines of each type etc., is user supplied. Subsequently, based on the results of each run, the modified HJ procedure makes alterations to the design variables. Each run is divided into two segments. The first segment is used to achieve steady state and data from this segment is discarded. The second segment is divided into ten batches in a way that the data is not auto-correlated. For each batch, a value of productivity is computed. The mean of the ten realizations and the corresponding standard error are used by the modified HJ procedure to generate alternate sets of decision variables. Only statistically significant improvements in productivity are recognized.

5. RESULTS

A partial output from the program appears as Table 3. It is seen that the program continuously seeks better sets of design variables by systematically searching the neighborhood of the starting point. For this problem, there were fourteen variables which were explored. Four variables (A-D) correspond to the number of machines of each type, four variables (E-H) correspond to the number of input buffers at each group of similar machines, four variables (I-L) correspond to the number of output buffers associated with each group of machines, one variable (M) corresponds to the number of AGVs in the system, and one variable (O) corresponds to the size of the central buffer. N is the number of alternate designs evaluated.

At the starting point (N=1), a productivity of 12.50 is achieved The first significantly better design is found at N=11 with a productivity of 13.40, and the optimum is identified at N=37 with a productivity of 13.68.

Note that at N=5, a productivity of 12.58 is achieved but is not identified as an improvement since statistical significance was not achieved.

Table 3: Progress of Modified Hooke-Jeeves Procedure

N	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*	*M*	*O*	*PROD*
1	*4*	*3*	*6*	*3*	*5*	*5*	*5*	*5*	*5*	*5*	*5*	*5*	*5*	*10*	*12.50*
2	6	3	6	3	5	5	5	5	5	5	5	5	5	10	11.78
3	2	3	6	3	5	5	5	5	5	5	5	5	5	10	10.64
4	5	3	6	3	5	5	5	5	5	5	5	5	5	10	12.17
5	3	3	6	3	5	5	5	5	5	5	5	5	5	10	12.58
6	4	5	6	3	5	5	5	5	5	5	5	5	5	10	11.72
7	4	1	6	3	5	5	5	5	5	5	5	5	5	10	4.78
8	4	4	6	3	5	5	5	5	5	5	5	5	5	10	12.17
9	4	2	6	3	5	5	5	5	5	5	5	5	5	10	9.89
10	4	3	8	3	5	5	5	5	5	5	5	5	5	10	11.59
11	*4*	*3*	*4*	*3*	*5*	*5*	*5*	*5*	*5*	*5*	*5*	*5*	*5*	*10*	*13.40*
12	4	3	4	5	5	5	5	5	5	5	5	5	5	10	12.11
13	4	3	4	1	5	5	5	5	5	5	5	5	5	10	6.50
14	4	3	4	4	5	5	5	5	5	5	5	5	5	10	12.82
15	4	3	4	2	5	5	5	5	5	5	5	5	5	10	11.72
16	4	3	4	3	7	5	5	5	5	5	5	5	5	10	13.44
17	4	3	4	3	3	5	5	5	5	5	5	5	5	10	13.19
18	4	3	4	3	6	5	5	5	5	5	5	5	5	10	13.39
19	4	3	4	3	4	5	5	5	5	5	5	5	5	10	13.24
20	4	3	4	3	5	7	5	5	5	5	5	5	5	10	13.34
21	4	3	4	3	5	3	5	5	5	5	5	5	5	10	13.36
22	4	3	4	3	5	6	5	5	5	5	5	5	5	10	13.38
23	4	3	4	3	5	4	5	5	5	5	5	5	5	10	13.27
24	4	3	4	3	5	5	7	5	5	5	5	5	5	10	13.37
25	4	3	4	3	5	5	3	5	5	5	5	5	5	10	13.26
26	4	3	4	3	5	5	6	5	5	5	5	5	5	10	13.37
27	4	3	4	3	5	5	4	5	5	5	5	5	5	10	13.31
28	4	3	4	3	5	5	5	7	5	5	5	5	5	10	13.24
29	4	3	4	3	5	5	5	3	5	5	5	5	5	10	13.35
30	4	3	4	3	5	5	5	6	5	5	5	5	5	10	13.36
31	4	3	4	3	5	5	5	4	5	5	5	5	5	10	13.38
32	4	3	4	3	5	5	5	5	7	5	5	5	5	10	13.24
33	4	3	4	3	5	5	5	5	3	5	5	5	5	10	13.22
34	4	3	4	3	5	5	5	5	6	5	5	5	5	10	13.36
35	4	3	4	3	5	5	5	5	4	5	5	5	5	10	13.32
36	4	3	4	3	5	5	5	5	5	7	5	5	5	10	13.13
37	*4*	*3*	*4*	*3*	*5*	*5*	*5*	*5*	*5*	*3*	*5*	*5*	*5*	*10*	*13.68*
38	4	3	4	3	5	5	5	5	5	3	7	5	5	10	13.44
39	4	3	4	3	5	5	5	5	5	3	3	5	5	10	13.26
40	4	3	4	3	5	5	5	5	5	3	6	5	5	10	13.15
41	4	3	4	3	5	5	5	5	5	3	4	5	5	10	13.42

6. CONCLUSIONS

A modified version of the HJ procedure has been developed to accommodate the stochastic nature of simulation. The procedure developed here provides a technique for using simulation with a generative procedure for identifying optimum designs of complex systems without full factorial experimentation. The application of this procedure is demonstrated through an example.

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