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Computer Controlled Optimization of a Rotary Vane Compressor

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INTRODUCTION

The compressor design process is a complex procedure for the design engineer. The designer must select values for the design variables, i.e., bore and stroke sizes, valve port diameters and locations, etc., to produce a compressor of specified capacity with highest Coefficient Of Performance (COP) and lowest cost. The interacting effects of the variables are not simple and thus determining the "best" values of the variables is a complex task. To analyze the compressor design, the designer has historically resorted to building a prototype compressor. Using his experience and intuition, designers successively modified the compressor and retested it. This "cut and try" sequence generally required several stages before an acceptable compressor was developed and it was expensive and time consuming. To reduce the amount of compressor testing and development time, compressor designers are using compressor modeling and simulations to reduce the amount of testing. The simulations allow the design engineers to evaluate design decisions quickly.

The logical next step in compressor design has been the use of univariate searches to attempt to optimize the compressor design in terms of improved performance or some other objective. It has been demonstrated employing univariate searches of the simulation program, that a design with improved performance can be determined. [1] The predicted performance improvement was verified experimentally on an actual compressor. [2]

Univariate searches consist of keeping all design variables fixed constant except one. The simulation is then run for different values of the free variable. The results are plotted and an optimum value of the free variable which maximizes the performance is found. Once the optimum value of the free variable is found it is fixed and the univariate search is repeated with another variable as the free variable. This process is then repeated until all variables have been searched. Univariate searches do not continously account for the interaction of design variables. After carrying out the univariate search on the second variable the optimum value from the first univariate search may no longer apply. A repeated univariate search on the first variable would generally produce a different optimum because of the interaction of the variables. Figure 1 illustrates the interaction of the variables. Point A is the optimum value found in a univariate search of variable X_1. Point B is the optimum value found in a subsequent univariate search of variable X_2. If a second univariate search of X_1 is made, the optimum will be shifted to point C. This point is still far from the true optimum for the two variables at point D. To achieve the true optimum it is more efficient to consider all the variables simultaneously with the variable interactions taken into account countinuously. Optimization or nonlinear programming technology permits an analysis of this type. Optimization algorithms minimize or maximize the objective function subject to a set of constraints on the design variable. The optimization problem is stated:

$$\begin{aligned} &\text{Minimize } f(x) \\ &\text{Subject to } g_i(x) \geq 0 \\ &\qquad h_k(x) = 0 \\ &\qquad i = 1,j \\ &\qquad k = 1,\ell \end{aligned}$$

The objective function and constaint functions can be highly nonlinear functions of several design variables thus making nonlinear programming, i.e., optimization an efficient way to consider the many variables of the compressor simulation. This paper presents the optimization of a rotary vane compressor as an example using a compressor simulation and an optimization routine.

COMPRESSOR SIMULATION MODEL

The simulation model of a rotary vane compressor[3] consists of a set of nonlinear differential and algebraic equations. The mass flow through the compressor is evaluated from a set of nonlinear differential equations of flow through compression chamber and the suction and discharge porting systems. The dynamic effect of the discharge valving is considered in the equations as well as losses due to internal leakage, frictional losses of bearings and the blades, and the viscous friction between the rotor and the rearhead and fronthead.

The compressor simulation integrates the differential equations with respect to time to obtain the mass flow, volumetric efficiency, power, COP, etc. For the rotary vane compressor simulation in this study numerical integration over one rotation of the rotor or two thermodynamic compression cycles requires approximately one minute on a C.D.C. 6500 computer system.

OPTIMIZATION-SIMULATION RELATIONSHIP

Figure 2 illustrates the relationship between the simulation and the optimization routine. The optimization routine actually controls the simulation and utilizes the output from the simulation to generate new values of the design variables based on the performance values. The performance criteria utilized is the standard COP given by the ratio of the cooling effect to the needed input power. The COP is a function of all the input design variables to the simulation program. Thus COP can be expressed as

$$COP = f(\alpha_i, \beta_i, \mu_i)$$

where α_i are the physical dimensions of the compressor, β_i are the refrigerant properties and μ_i are variables specifying the compressor operating conditions. In this optimization process only changes in the physical dimensions are considered and not the refrigerant properties or operating conditions.

OPTIMIZATION METHOD

The selection of the optimization routine is an important decision. Because the compressor simulation requires one minute of computer time per evaluation of COP, an algorithm that requires a minimum number of performance function evaluations is most appropriate for the optimization. A method that allows constraints between the design variable to be considered is also necessary.

A review of optimization literature indicates that many constrained optimization methods are available [4,5]. The methods fall into two categories, direct methods and indirect methods. Indirect methods combine the constraint functions and objective function into a penalty function in the general form

$$P(x,w) = f(x) + \frac{1}{w}\left[\sum_{i=1}^{j} g_i^2 + \sum_{k=1}^{\ell} h_k^2\right]$$

for $g_i < 0$

The penalty function is minimized in a series of steps. Each step is a minimization and the penalty parameter, w, is reduced for each subsequent minimization until no improvement in the optimum is realized.

Direct methods are algorithms designed to consider constraints in the algorithm logic. The direct methods will thus, in general, use fewer function evaluations in obtaining an optimum. The various methods have been tested and the GRGDFP method was shown [6] to use the minimum number of function evaluations.

GRGDFP is a combination of generalized reduced gradient method [7] of handling constraints and the Davidon-Fletcher-Power [8] unconstrained search method. In the algorithm, the inequality constraints are reformulated as equality constraints by the addition of slack variables, X_S, as follows:

$$g_i(x) - X_s = 0, \text{ where } X_s \geq 0.$$

Bounds on variables are not reformulated as equality constraints.

The variables are then divided into two groups called decisions and states. There are as many state variables as constraints in the original problem. The number of decision variables is the total number of variables, slack and design, minus the number of constraints, or equivalently the number of decision variables is the number of design variables minus the number of original equality constraints. The decision variables are free to change and the state variables are adjusted to maintain constraint feasibility. The algorithm uses the Davidon-Fletcher-Power method to search the decision variables for an optimum of the objective function while the constraints are kept feasible by the state variables.

COMPRESSOR OPTIMIZATION

Figure 3 is a schematic drawing of the example rotary vane compressor. The compression process takes place as the rotor turns in the direction shown. The refrigerant is drawn into the cylinder on the suction side through the suction ports. As the rotor turns the volume of refrigerant is swept to the discharge side of the compressor where it is compressed and forced out of the discharge ports. The first optimization was conducted using five geometric design variables considered to have a significant influence on the compressor performance. The constraints considered were upper and lower bounds on each of the variables, two inequality constraints involving functional relations between the selected design variables and other design variables (constants in the analysis), and an equality constraint to maintain a constant swept volume. The constant swept volume constraint was a first order constraint on maintaining a constant capacity. One of the inequality constraints, for example, prevented the suction and discharge ports from being open to the same compression chamber. Figure 4 shows the progress of the optimization. The program carried out five iterations and produced an improvement of 1.82% in the COP. It would appear that the compressor design is almost optimal in terms of the five design variables first selected. The five-variable optimization revealed a problem in using the simulation. The GRGDFP method approximates the gradient of the objective function with forward difference methods. The algorithm uses the gradient to determine a search direction and as a convergence criteria. The gradient length is a measure of how close the search is to the optimum since the gradient approaches zero at the optimum. The approximated gradient becomes inaccurate due to "noise" in the simulation and thus useless for determining a search direction and the search is stopped. This can be seen in Figure 5 where at iteration five the gradient length becomes very large.

The "noise" is an error in the COP value from the simulation program. The COP value can be thought of as a sum of an exact COP plus typical errors due to roundoff, truncation, etc. The "noise" is a function of the initial conditions beginning the simulation integrations. The initial conditions cause an error because the integration of the simulation equations is stopped after only two thermodynamic cycles. The results are sensitive to the initial conditions chosen when steady state conditions have not been achieved before integration is stopped. To relieve the "noise" problem, the forward difference step size was increased to the order of magnitude of the machining tolerance and to improve the initial conditions the final conditions for each simulation evaluation were retained and used as the initial conditions for the next evaluation, assuming relatively small changes in the compressor design variables. However, these changes did not completely eliminate the problem of "noise."

The next optimization was conducted with thirteen geometric design variables; the original five variables plus eight additional considered to have some lesser effect on compressor performances. The constraint on the compressor design again consisted of upper and lower boundaries on each of the design variables, the one constant swept volume equality constraint, and seven inequality design constraints, i.e., the discharge port was not allowed to become larger than one half the cylinder height.

Figure 4 shows the results of the thirteen variable optimization with a 5% improvement in performance. It is obvious that considerable additional improvement was obtained by permitting the variation of more design variables in the search for the optimum. Searches of this scope would be extremely laborious without the use of a machine automated search process. Figure 5 again presents the convergence criteria - gradient length for each iteration. This optimization was stopped at the ninth iteration by noise maintaining the gradient to an irredricible level.

CONCLUSIONS

The research shows that optimizing compressors using simulations and direct search routine is useful. For both the five varaible optimization and the thirteen variable optimization an improved design was obtained.

Compressor simulations require a large amount of computer time for each evaluation of the performance value. Therefore the optimization routine must be carefully considered. The optimization routine should use a minimum number of performance function evaluations to minimize total computer time.

Optimization not only produces a better design but it also provides the designer with new insights into the relationship of the design variables at the optimum design. Optimization will also indicate any modelling difficiencies in the simulation program and emphasize the relationship of the constraints to the optimum design.

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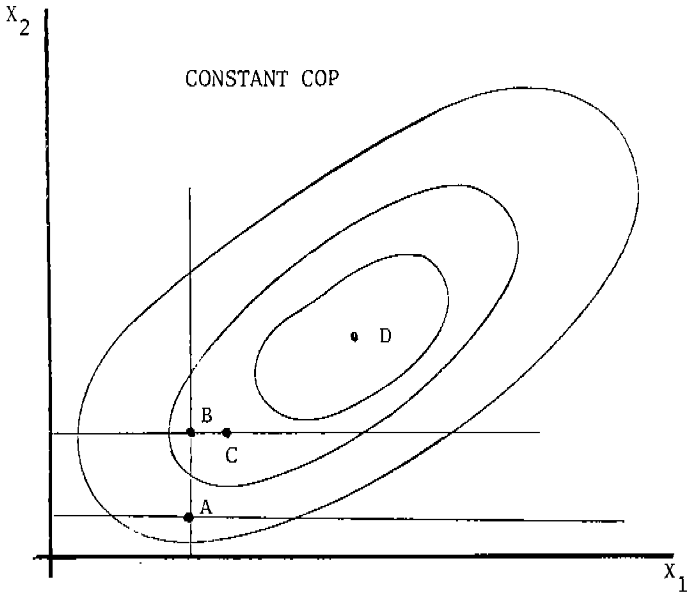

FIGURE 1
OPTIMIZATION BY UNIVARIATE SEARCHES

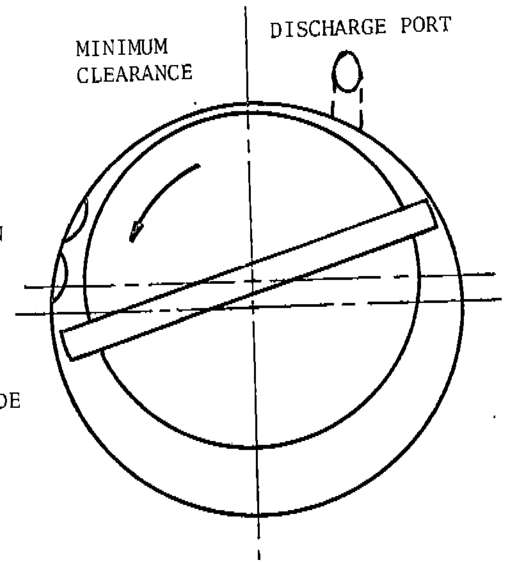

FIGURE 3
TOP VIEW OF ROTARY VANE COMPRESSOR

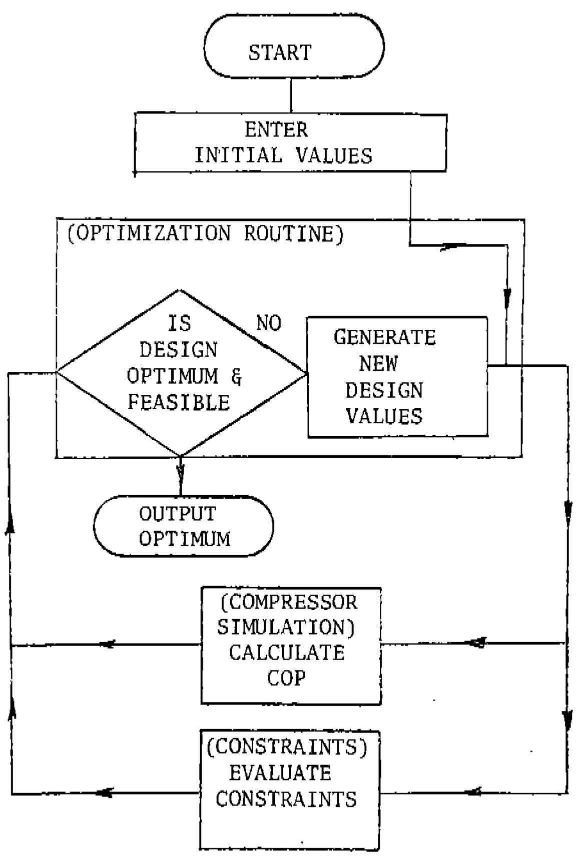

FIGURE 2
RELATIONSHIP BETWEEN OPTIMIZATION
ROUTINE AND SIMULATION

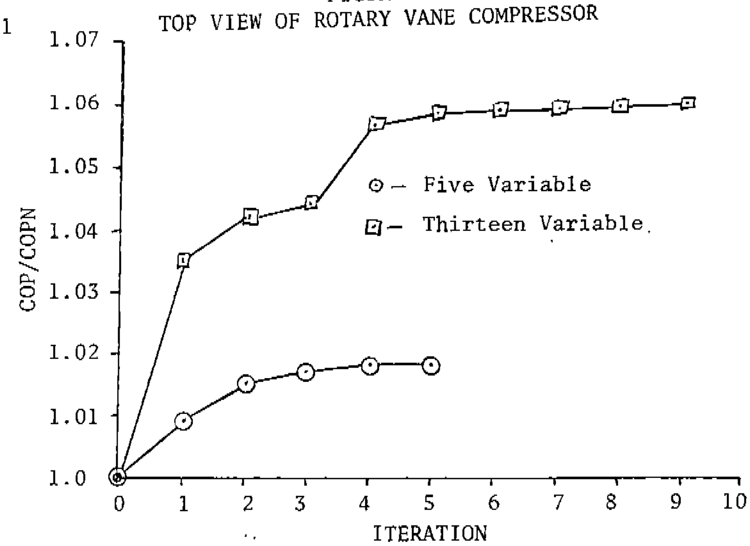

FIGURE 4
PERFORMANCE IMPROVEMENT FOR FIVE AND THIRTEEN
VARIABLE OPTIMIZATION

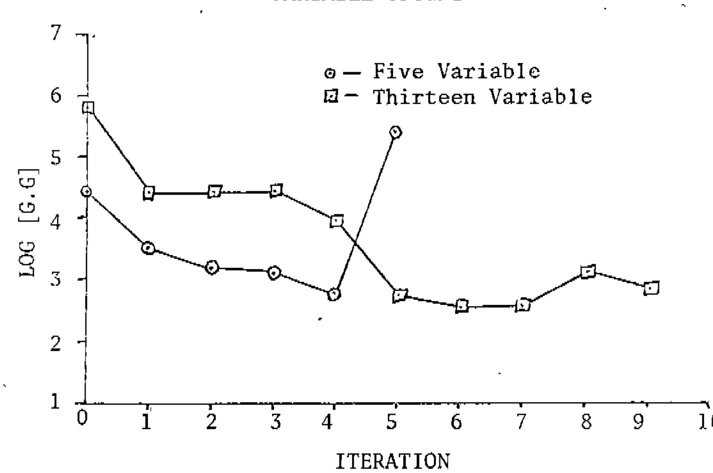

FIGURE 5
LOG CONVERGENCE CRITERIA [G.G] VS ITERATION
FOR FIVE AND THIRTEEN VARIABLE
COMPRESSOR OPTIMIZATION