The optimization of an industrial pneumatic supply system

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Abstract

Pneumatic supply systems provide the high quality, high-pressure air used in industrial settings. They can consume significant amounts of energy as well as requiring significant capital investment in equipment, whereas an optimum selection of components and other design considerations can result in significant savings. The objective of this work was to investigate the use of Differential Evolution (DE) to help design a pneumatic supply system based on a selection of components from a component database. This design ensured that as many individual components were used, in series or parallel, to provide the desired pressure and flow rate. The use of a database to select components is of special interest as it is characterized by a discrete, and hence non-differentiable, variation between component performances. DE was used to systematically, and efficiently, find the best combination of components that was least expensive for the payback period under consideration. One outcome of this work is a modification to DE that allows us to reliably determine not only the best combination, but also the N-best solutions. An interesting and unexpected result, for the system we considered, was that as the payback period got longer, the best system switched from a single compressor system to a dual compressor system.

Keywords: Differential Evolution (DE), genetic algorithms, optimization, evolutionary algorithms, pneumatic supply, compressed air, and design.

1 Introduction

The objective of this work was to obtain a better understanding of the optimization of engineering design problems which contain discrete parameters. The application of modern, computer based optimization methods to engineering
design is relatively new, due to earlier limitations in numerical simulation codes, optimization algorithms, and computer technology. As such, we have limited experience with the subject, and considerable work needs to be done to understand the complex interactions that may occur, or for that matter practical issues that deal with how we pose the optimization question. A deeper understanding of the interactions is particularly important for problems with large numbers of degrees of freedom or discrete and integer variables. These interactions stem from how a problem is modelled, parameter type, and specific code and problem issues. The use of parameterization is often necessary as a means of reducing the scale of the problem to a manageable size. For example, the determination of an airfoil cross section where the shape is defined by a parametric curve with a limited number of parameters instead of dealing with an infinite number of degrees of freedom determining the location of each point on the surface. The issue variable type naturally arises due to the discrete and integer character of most engineering problems such as material properties, or the number if parts to use.

So far, the majority of published engineering optimization papers have focused on problems that have continuous variables such as the determination of optimum airfoil shape. In depth discussions of continuous variable airfoil design can be found in Liebeck [1] and Rogalsky, et al [2]. Problems with integer or discrete variables are much harder to find, but a few examples can be found in the work of Lampinen and Zelinka [3].

The problem that was chosen for this work is the design of an industrial pneumatic supply system from catalogues of existing components. In order to keep the specific problem tractable for the purposes of this study several limitations in scope and degree of complexity had to be made. The main limitation being that the components would be selected from a small design catalogue. Complexity was reduced by simplifying the cost calculations by neglecting the cost of the connecting piping and installation, financing, and so on. We believe that this model is sufficient for the purposes of this study, while it is inadequate for design purposes.

1.1 Pneumatic supply systems

Compressed air is a very important power source in industry, and is used to drive a wide variety of machines. These machines range from painting and cleaning equipment, pneumatic tools, motors, to very large presses and shears. This paper will focus on the production of compressed air, the supply side, and will not consider how it is distributed and used, the demand side. The reader who wants to learn more about these systems is directed to the texts by Rollins [4] or Pinches and Callear [5].

The demand side will be characterised using statistical measures of the flow rate required and is a necessary design input. These measures are defined in three main flow regimes; peak, base and off-hours. Peak flow is defined as the largest typical flow requirement that can occur during any shift. It may arise at the start of a shift, right after coffee break, or during a high demand operation. Base demand can be thought of as the average consumption rate one would see
during a regular shift. Off-hours demand is the type of demand one may see during a weekend shift or during low production runs. Sudden short duration demands can exist within the main flow regimes; surges, spikes, and maximum flow. A surge occurs when the demand exceeds the total flow capacity of all currently operating compressors, a spike occurs when total demand exceeds the total capacity of all compressors, and maximum flow is the maximum possible instantaneous flow rate.

The main element of a pneumatic supply system is a bank of one or more compressors, and may be the sole component in a very simple system. There are three main types of compressor that are typically used, piston, vane, and screw. The characteristics of each are not important here, so an arbitrary choice was made to limit consideration to screw type compressors. The compressors are most often driven by electric motors and will be assumed to be included equipment. This does have an impact on the design calculations as electric motor life limits the frequency of starts per hour, or the minimum length of time the motor must run. The cost of compressor and motor development is such that these components will usually be considered supplied equipment and be selected from manufacturer’s catalogues with little if any customization.

![Figure 1: A schematic layout of the components of a pneumatic supply system.](image)

As shown in figure 1, most systems also include a receiver, which is a tank used to store a volume of compressed air, and a flow controller. This is an important method of smoothing out compressor generated pressure fluctuations for painting applications and acting as an accumulator for power applications. A flow controller allows the receiver to store air in the receiver at a higher pressure than is required on the demand side. This results in a reduction in overall consumption by allowing a reduction in demand side leak rates, and a reduction of operating cost through a more efficient supply system. The significance for power applications is clearly demonstrated if we consider the operation of an
actuator, or pneumatic cylinder. The actuator will use a fixed flow rate of air at a given pressure during its operation. If the compressor is sized to meet this duty itself, it would waste, or blow off, all of the energy it produced during the off operation time. However if a smaller compressor, with lower flow rate, was selected that could continuously store enough energy for the actuator’s operation it would be more efficient, and the smaller size correlates with a much less expensive machine, reducing capitol costs. As with the compressor, the flow controller is usually selected from a catalogues, while it is not unreasonable to design and build a custom receiver tank.

The source of air is usually the atmosphere, which is moist, contains dust, and possibly other contaminants. The moisture can result in condensation problems in the compressed and can result in corrosion, damaged tools, and poor paint quality. To deal with these issues; the air is usually conditioned using dryers and a variety of filters. Each device adds to the capitol cost and to the system operating cost through filters, supplies, and labour. This study only considered the cost of filters and supplies, and capitol costs.

1.2 Design of pneumatic supply systems

The design of a pneumatic supply system from scratch is a difficult problem, as we must forecast the expected demand that a system will have over a period of time. This is very difficult if the system will be used to introduce pneumatic power to a plant, but is simpler if it replaces an existing system, as the demand will be better understood. In either case, one must speculate on the future expansion of demand. This can have an impact on performance, but is outside of the scope of this paper.

The system demand characteristics form the basis of the design and constrain the design. One must identify critical requirements, and insure that the supply can meet the demand that associated with them. For example, intermittent shortfalls in the supply of compressed air can slow down a production line if tools fail to operate, or safety can be compromised if there is a shortfall during a critical time. These constraints do have a cost, either by reduced productivity or liability, but will not be considered part of the costs of the design.

The typical performance requirements placed on the design will be that it has the best economic performance, not that the system uses the least power or other factor. Designs are often optimized for least capital cost, particularly if the design was for a manufacturer who does not operate the system themselves. While users, on the other hand, will want a system that has the lowest capital and operating cost over a reasonable expected life, or payback, time. This paper takes the view of a user and considers both capital and operating costs.

Component selection from existing catalogues is the typical approach to construct the design. The development costs to design a compressor are very large and almost never justified. As such the compressor performance has to be treated as having discrete performance. This is also true of the pre-filters, dryers, and so on. Our approach for selecting the receivers was to determine a
dynamically sized volume and require that the receiver selected from a database to be equal or greater than the required volume.

1.3 The cost of a pneumatic supply system

The cost of a pneumatic supply system comes from three main sources; capitol costs, operating costs, and financing costs. Clearly the capitol cost is the sum of the cost of each component, interconnections, space and fabrication costs; it is easy to analyze and obtain precise estimates. This paper will only consider the component costs for simplicity. Operating costs include the price of all consumables (such as filter elements), power, and maintenance costs. This is more difficult to determine accurately in all cases, but is estimated from typical, manufacturer’s recommendations. One should note that particularly dirty environments could result in a much greater use of filter elements than that in a typical application. The financing cost is the costs incurred from interest and reduced opportunity, and is outside the scope of this work.

1.4 Pneumatic system optimization

Current engineering practice and objectives for system optimization depend on whether the system is an existing system or is for an entirely new system. Optimization of existing systems starts with a search for and plugging of all of the existing leaks and may not require a new selection of components. Our interest was in the design of an entirely new system where all of the components will be selected.

At present, limited searches form the basis of most new designs. A designer will use the catalogue of a few trusted suppliers, to provide a few basic design configurations. The performance will be estimated to determine if the maximum demand profile can be met, and the system with the best cost will be selected. This is usually done with ‘hand’ calculations so very few designs will be considered due to time constraints. As such, the resulting pneumatic supply is not the global best system for the application, but merely one that meets expectations with acceptable performance. We can do much better if modern optimization methods are used to perform a more exhaustive search.

Reliance on heuristics also forms an important part of current design practice, such as using one US gallon of receiver size for each standard cubic foot per minute (scfm) of compressor capacity. This and other heuristics simplifies the design process and usually provides acceptable function, but will not result in an optimum system.

2 The optimization problem

The particular problem selected for this work was simplified to demonstrate the application of DE to a design problem that utilized a discrete catalogue of components as is often found in engineering. The solution is simplified and cannot be considered as adequate for actual design purposes.
Program limitations result from not considering the costs of the interconnections and fabrication, maintenance labour costs, and any of the financing costs. These costs can be substantial and would have to be considered for a real design.

2.1 Simulation of design performance

2.1.1 Component selection
A data base approach was used to specify the individual component’s characteristics. The data base structure enumerates each component an associates the basic performance of each, and is tailored to its type. For example, a compressor would have its cost, pressure, flow rate, and power consumption specified. While a filter would list cost, pressure drop, flow rate, filter element replacement rate and cost. The number of components in each database was kept small to reduce CPU time, but should result in similar optimization characteristics of much larger databases.

The number of each component required for a design was set to meet the system constraints. For example two compressors in parallel would be used if the design considered a compressor that produced half the required capacity. Similar design choices were made with other devices. The size of the component was randomly selected, but the number of each specific component was incremented to meet the requirements of the system. For example, the filters had to have a minimum throughput that met the total compressor capacities. When multiple components were required, they were assumed to be installed in parallel because this is the best way from an operational cost perspective and it would be done this way in industry.

2.1.2 Receiver volume determination
The design code used a simple formula to determine a minimum acceptable receiver size rather than relying on the previously mentioned heuristic. The calculation determines the volume necessary to supply a demand spike of \( C \) scfm for \( t \) minutes duration, where the receiver pressure changes from \( P_1 \) to \( P_2 \), and is given by

\[
V = \frac{CtP_0}{P_1 - P_2}
\]

where \( P_0 \) is the atmospheric pressure, and \( V \) is the volume in cubic feet.

2.1.3 Cost analysis
As stated previously capitol costs were determined from the sum of all the components costs, and did not include connections and fabrication. As well the operation costs are based solely on power and the manufacturer’s recommendations for consumable use under typical conditions.
2.2 Differential evolution

DE is a specific example of a genetic optimization algorithm that was developed and promoted by Kenneth Price and Rainier Storn. A thorough description of it can be found in Price [6]. Its signature feature is that the population of each generation is used to generate the random variables required for a genetic approach.

The main advantages of DE are that it is easy to use and modify, it is effective and efficient, its precision is only limited by floating point format, does not require cost function differentiability, uses only self referential mutations, is inherently parallel, and works with noisy, epistatic and time dependent cost functions. It has a good history of success at effectively determining the global optimum for a wide range of problems.

2.2.1 The basic method

DE is a simple process that takes an initial population of designs and applies concepts from evolution to produce subsequent generations that have elements that migrate to the optimum. The initial population is randomly selected from throughout the design space and serves as a starting point. The pneumatic supply problem has each member described by its DNA, which is a combined list of each component’s identifier number.

Each population or generation is then modified by mutation and combined with other elements to form a child population. The next generation is formed by selecting the winner of a tournament between child and parent.

The mutation operation used by DE is unique in that it is obtained from data contained within the current generation. A parent in mutated by randomly selecting two other population members to form a random difference and adding $F$ times that difference to the parent. The factor $F$ scales the mutation and is a tuneable input to the process.

The next step is the recombination process used to produce child members, and combines the elements of the parent DNA with that of another randomly selected member by selecting either element based on whether a random number is greater or less than $K$, a tuneable cross-over factor between 0 and 1. At least one element is selected from the random parent.

This process is iterative and continues until the stopping criteria are met. This can either be the creation of a set number of generations, or when the value of the objective function of the fittest member of each generation converges to a specified tolerance.

Several versions of DE exist. The most commonly used applies a further modification of the mutation by biasing the mutation by $F$ times the difference between the best population member and current population member.

2.2.2 Modified differential evolution

As engineering design specification is often difficult to specify precisely and that a wider range of choices is required, we often want to know the $N$-best designs for a particular application. While DE is very effective at finding the best
solution, it often failed to reliably determine the second, third, and so on best solutions. This required a modification to DE to alleviate this.

The modification is relatively simple and is based on the biasing to the optimum. Rather than use the population member with the best objective function value to bias the mutation, a list of the $N$-best solutions is used. The bias for a given parent was then obtained by randomly selecting an element from the $N$-best list.

### 3 Results and discussion

The size of the data bases allowed us to perform a complete search of all possible combination of components to determine the $N$-best combinations for a variety of demand profiles and number of years for the pay back period. This allowed us to determine the relative performance of the optimization process. Three issues were examined: the influence of $F$, $K$, and population size on the reliability and efficiency of DE, the effectiveness of modified DE, MDE, in determining the $N$-best solutions, and to gain insight into the application of DE on the design.

Population sizes were tested at increments of 60, from 120 to 3000 members. Each population size was tested on up to 4,060 unique demand profiles which were defined to cover the full range of the databases, and represented 4,060 separate and unique industrial compressed air demand profiles. In order to speed data collection, MDE was required to converge to all $N$-best values within an arbitrary ceiling of 8,064,000 cost function evaluations. This number matched the complete comparison of all possible parameter combinations for the test program.

If MDE failed to converge within the arbitrary ceiling to the $N$-best for any one of the 4,060 input variations during the testing of a given population size, convergence was deemed to have failed and the data was discarded. Upon successful convergence for all 4,060 input variations or failure for one, the population size was incremented and the inputs began again from the initial settings. Figure 2 shows the results of the data collection for a search for the 10-best designs.

The results of this test program showed that the optimum system changes from favoring single compressor systems to dual compressor system when longer time intervals were examined. This is not what an engineer would intuitively expect, and indicates the importance of DE as a design tool.

Each point in figure 2 represents the average number of function evaluations it took to converge to the ten best solutions in 4,060 unique tests of a given population size.

The tested values of $F = 0.5$ with $K = 0.5$ failed to converge within the arbitrary ceiling for at least one of the 4,060 input variations for each population size tested; thus the absence of representative data for that setting. Similarly, the absence of data depicting a setting of $F = 0.8$ and $K = 0.6$ is due to the same cause.
The results indicate the limits on the values of $F$ and $K$ that can ensure convergence under the test conditions. It is quite likely that exact limitations will be problem specific and others will find success with different population sizes than those shown Figure 2. However, it is expected that the general influence of $F$ and $K$ will remain the same.

In general, increasing the value of $K$ increases convergence rate but requires a larger population to ensure converge consistency under testing. Increasing the value of $F$ has the opposite effect; moreover, increasing the population size tends to slow convergence.

The setting of $F = 0.8$ and $K = 0.45$ proved to be the best setting for this problem. This setting, coupled with a population size of 1620 members, converged to the ten best solutions at a mean of less than 40,000 function evaluations for all inputs tested. This compares very favorably to the 8,064,000 function evaluations required for to test all possible combinations and demonstrates the power of DE.

4 Conclusions

The results of this work clearly show the beneficial value of MDE for design optimization. The method maintains the speed and properties of DE, and
reliably retrieves the $N$-best solutions to the component selection. The $N$-best multiple solutions allow the designer choice without having to code preference into the objective function. Ultimately, the designer can easily select the most effective combination of components without giving up the flexibility of preference.

The results demonstrated that DE and its offspring MDE can result in the natural discovery of non-intuitive solutions to a design optimization. This was demonstrated by the finding that the optimum number of compressors would change as the study period increased, using current design methods most engineers would assume that number to be constant. We have concluded that DE and MDE are the most appropriate choice for the construction of design optimization codes.

This article also demonstrated that increasing the value of $K$ increases convergence rate but requires a larger population to ensure convergence consistency. Increasing the value of $F$ has the opposite effect and increasing the population size tends to slow convergence. These findings should be valid for any version of DE but the precise values of $F$, $K$, and population size that prove the most effective will be problem specific.

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