Optimization of Fuel Consumption in Compressor Stations

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Summary
Natural gas passing through pipelines is transported by means of compressor stations that are installed in pipeline-network systems. These stations are usually installed at intervals greater than 60 miles to overcome pressure loss, and typically, they consume approximately 3 to 5% of the transported gas, making the problem of how to optimally operate the compressors driving the gas in a pipeline network important. The objective function of the optimization model is a nonlinear mathematical relationship. The model has been studied to minimize the fuel consumption in the compressor stations and to obtain suitable decision-making variables. Genetic algorithms are used as the optimization methodology, and the software program Lingo (Thompson 2011) is used to compare the optimization results. Two cases of centrifugal compressor stations with different performances are studied. The optimization model aims to improve the fuel consumption of the compressor stations in the pipeline network according to the conditions of the transmissions.

Introduction
Gas-transmission systems have been used for decades to transport large quantities of natural gas across long distances by means of compressor stations. Therefore, natural-gas compressor stations are located at regular intervals along the pipelines to compensate for pressure loss. These compressors consume a part of the transported gas, which results in an important fuel-consumption cost. Therefore, optimization of fuel consumption plays an important role in the operating costs of the stations. The difficulties of such optimization problems arise from several aspects. First, compressor stations are very sophisticated entities that may consist of a few dozen compressor units with different configurations, characteristics, and nonlinear behavior. Second, the set of constraints that defines feasible operating conditions in the compressors, along with the constraints in the pipes, constitutes a very complex system of nonlinear constraints.

Flores-Villarreal and Rios-Mercado (2003) extended a study by means of an extensive computational evaluation of the generalized reduced-gradient method to obtain a fuel-cost-minimization problem. Borraz-Sánchez (2010) discusses the method of minimizing fuel cost in gas-transmission networks by dynamic programming and adaptive discretization. Goldberg and Kuo (1985) provide genetic algorithms that were used for the first time for the optimization of the pipelines. Odom and Muster (1991), members of a solar-turbine manufacturing corporation, presented two diverse versions for modeling gas turbines that activate centrifugal compressors. Andrus (1994) wielded spreadsheets for the first time to simulate the steady-state gas-transmitting pipes and network, stipulating that the compressibility factor is constant for all the systems. The aforementioned methodology was executed once again by Cameron (1999) to examine both steady and transient flows in Excel software. Chapman and Abbaspour (2003) developed fuel-optimization methodologies in compressor stations in nonisothermal and transient conditions with compressor-shaft velocities as a decision-making variable.


Gosling et al. (1994) showed that gradient-based optimization methods have been used to analyze gas-pipeline networks in the past. As the name implies, they rely on the derivative of the function being optimized with respect to all control variables that define the system. There are several gradient-based optimization methods, depending on the nature of the objective function and associated constraints (i.e., constrained and unconstrained linear programming, quadratic programming, and NLP). An extensive review of these methods and available software tools can be found in More and Wright (1993). Tsai et al. (1986) showed that dropped particularly close to the operation boundaries, often trapped in local minima and very dependent on the starting point. These methods have also been extended to transient pipeline optimization, but only on relatively smaller systems. Hawryluk et al. (2010) studied optimizations that were based on dynamic programming (e.g., based on Bellman’s optimality principle). Habibvand and Bebhahani (2012) showed the optimization of the fuel consumption of the compressors through manipulation of the affecting parameters of the compressors and the operating-condition parameters of the turbines and the air coolers within a gas-compression-station unit in operation phase by use of a genetic algorithm.

Jenicek and Kralk (1995) described an optimization system for local control of compressor-station operation. The compressor-station topography is arbitrary, and the configuration of compressors was assumed to be fixed, while each compressor unit was described by its individual characteristics. The optimization was performed as a steady-state optimization, and the criterion used was represented by a total of the consumed energy or a total of the price for the consumed energy.

Wright et al. (1998) discussed simulated annealing as a technique for finding the optimum configuration and power settings for multiple compressors when the number of compressors is large. The simulated-annealing technique derived from statistical mechanical considerations.
was used to find the “best-use” mode of their operation. Tests of simulated annealing against the more ubiquitous MINLP and heuristic techniques were performed.

Jin and Wojtanowicz (2010) discussed the optimization of a large gas-pipeline network—a case study in China that aimed to optimize the network to minimize its energy consumption and cost. The large size and complex geometry of the network required breaking the study down into simple components, optimizing operation of the components locally, recombining the optimized components into the network, and optimizing the network globally. This four-step approach used four different optimization methods—penalty function, pattern search, enumeration, and nonsequential dynamic programming—to solve the problem. The results showed that cost savings because of global optimization were reduced with increased throughput.

The purpose of this paper is to minimize the fuel consumption in the compressor stations with a nonlinear mathematical relationship as the objective function. Genetic algorithms are used as the optimization methodology. The genetic algorithm is a relatively new optimization method and serves well as an optimization tool. This is because the nature of the variables involved is made of continuous and discrete variables that can change several parameters simultaneously, and its use in the pertinent nonlinear problem does not make it entrapped in the local-optimum spots. Two cases of centrifugal compressor stations with different performances are shown in Fig. 2.

Problem Formulation

Centrifugal Compressor. Habibvand and Behbahani (2012) showed that the governing quantities of a centrifugal compressor unit are inlet volumetric flow rate \( Q \), speed \( S \) (rev/sec), adiabatic head \( H \) (ft-lbf/lbm), and adiabatic efficiency \( \eta \). It has been recognized that the relationship among these quantities can be described by the following two equations:

\[
\frac{H}{S^2} = A_h + B_h \left( \frac{Q}{S} \right) + C_h \left( \frac{Q}{S} \right)^2 + D_h \left( \frac{Q}{S} \right)^3 \quad \text{..............(1)}
\]

and

\[
\eta = A_e + B_e \left( \frac{Q}{S} \right) + C_e \left( \frac{Q}{S} \right)^2 + D_e \left( \frac{Q}{S} \right)^3 \quad \text{..............(2)}
\]

where \( A_h, B_h, C_h, D_h, A_e, B_e, C_e, \) and \( D_e \) are constants that depend on the compressor unit and are typically estimated by applying the least-squares method to a set of collected data of the quantities \( S \) (rev/sec), \( H \) (ft-lbf/lbm), and \( \eta \).

Figs. 1 and 2 show the set of data collected from a typical centrifugal unit. Fig. 1 represents \( H \) (ft-lbf/lbm) vs. \( Q \) (ft³/sec) at different speed values for \( S \) (rev/sec) between \( S_{\text{min}} \) and \( S_{\text{max}} \) in Fig. 2. A plot of Eq. 2 is illustrated in Fig. 2.

Woldeyohannes and Majid (2011) showed that the relationship between \( H \) (ft-lbf/lbm), suction pressure \( P_s \) (psia), and discharge pressure \( P_d \) (psia) is

\[
H = \left( \frac{k}{k-1} \right) ZRT \left[ \left( \frac{P_s}{P_d} \right)^{rac{1}{k-1}} - 1 \right] \quad \text{..............................(3)}
\]

The power of the compressor can be computed by the following relation:

\[
PWR = \frac{32174 \times W \times H}{\eta \times \eta_{\text{mech}}} + AI \quad \text{..............................(4)}
\]

Centrifugal compressors have been bounded within choke/stone-wall limits at the bottom of the map and surge and stall scope at the top of the map and at the minimum and maximum shaft-rotation speed.

Compressibility-Calculation Procedure. Mallinson et al. (1986) show that the compressibility of natural gas through pipelines and compressor stations can be estimated from the following equation:

\[
Z = Z_0 + aP + bP^2 \quad \text{..............................(5)}
\]

\( Z_0, a, \) and \( b \) are constants derived from a virial series expansion (Eq. 5) for \( Z \) on the basis of the Redlich-Kwong equation of state, and are dependent upon the gas temperature and the pseudocritical pressure and temperature.

The virial series expansion for compressibility is

\[
Z = Z_0 + \left( Z_1 B + Z_2 A^2 \right) P + \left( 3Z_1 B A + Z_4 A^4 \right) P^2 \quad \text{..............................(6)}
\]

\( A \) and \( B \) are constants that depend on the gas temperature and the pseudocritical pressure and temperature. The constants \( a \) and \( b \) are \( a = Z_1 B + Z_2 A^2 \) and \( b = 3Z_1 B A + Z_4 A^4 \). The values of \( A \) and \( B \) are \( A^1 = V S T_{c,1}^{1.5} \left/ P_c T \right^1 \) and \( B = V S T_{c,1}^{2.5} \left/ P_c T \right^2 \).

Gas Turbine. The gas turbine generates the required power for the compressor. Habibvand and Behbahani (2012) showed that the required \( PWR \) (ft-lbf/sec) of the compressor is used to compute the generating power of the gas turbine and the fuel-consumption rate. The quantity of fuel consumption (FC) of the gas turbine in scf/sec can be computed as

\[
\text{FC} = \frac{PWR}{\text{PWR} / \text{FC}} \quad \text{..............................(7)}
\]
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• Genetic algorithms use objective-function information (evaluation of a given function by use of the parameters encoded in the string structure), not derivatives or other auxiliary information, to guide the search.
• Genetic algorithms use a coding of the parameters that are used to calculate the objective function in guiding the search, not the parameters themselves.
• Genetic algorithms search through many points in the solution space at one time, not a single point.
• Genetic algorithms use probabilistic rules, not deterministic rules, in moving from one set of solutions (a population) to the next.

The advantages of using genetic algorithms can be discussed from several perspectives:

- The design space is converted into the genetic space, which is the encoded space in this algorithm. Thus, it will become feasible to transpose the incessant huge spaces into disjointed tiny spaces that are used to solve the optimization quandary here.
- A genetic algorithm interacts with a particular set of points, whereas we focused on a specific point in most optimization methods. In other words, genetic algorithms process multiple possible responses that eventually enable us to access the available optimum responses at the end of optimization.
- This algorithm is based on the guided haphazard process; therefore, its use in the pertinent nonlinear problem does not make it entrapped in the local-optimum spots.

The trend of this algorithm can be displayed in accordance with Fig. 3. An abstracted sample of candidates for solving (chromosomes) can claim a better solution in such algorithms. The design space has been created with a random populace of strings (0 and 1 here), and these strings recur in generations.

![Fig. 3—Genetic-algorithm-optimization procedure.](image-url)
The optimized results are obtained on the basis of one of these prevalent stoppage criteria:

1. The number of generations procreated; the maximum number of generations (300) is reached.
2. The convergence of the error criteria. There is no improvement in the objective function for a sequence of 100 consecutive generations.
3. There is no improvement in the objective function during an interval of 50 seconds.

The methodology acts as the corresponding quantities of the decision-making variables of the problem alter their nature incessantly between the genetic space code and the response. The response space can be identified either as diverse numerical combinations different from the decision-making variable or the velocity of the compressors available in the network.

The code space is made up of the binary-structured chromosomes. The \( k \) quantity is computed on the basis of the difference of the velocity limitations of each chromosome to determine the length of chromosomes available in this space.

\[
j = \{s_1^i, s_2^i, \ldots, s_k^i\} \quad \text{-------------------------------------------(14)}
\]

The methodology acts as the corresponding quantities of the decision-making variables of the problem alter their nature incessantly between the genetic space code and the response. The response space can be identified either as diverse numerical combinations different from the decision-making variable or the velocity of the compressors available in the network.

There are \( k \) bits required to encode \( Sd \) in the binary-coding methodology. The response chromosomes will be depicted eventually as Fig. 4.

Here, we have stipulated the \( k_i \) quantities equal to each other and counterpoised to the largest one. Each \( s \) can be computed on the basis of the ensuing formula:

\[
s_i = s_i^l + \frac{Sd_i}{n \times k_i} \quad \text{-------------------------------------------(18)}
\]

Diverse methodologies can be envisaged for operators available in the code space. Here, the tournament method is used for the reproduction operator in this particular quandary. In other words, a small set of chromosomes are picked out haphazardly to compete with each other. One of the chromosomes is copied as a generator in the mating pool on the basis of the objective function or the evaluation score. Then, the crossover operator acts upon the chromosomes available in the mating pool in accordance with the two-point cut methodology, and the contents of the two chromosomes are swapped by singling out two indiscriminate spots, as in Fig. 5.

It should be noted that the crossover operator rate and the mutation operator rate are 0.6 and 0.01, respectively, after several reiterations of the experiment in this study.

Case Studies

This is a case study of compressor stations to obtain the optimal speeds of all six active compressors simultaneously, and consequently to obtain the minimum fuel-consumption rate. The following data are given by the Egyptian Natural Gas Co. (GASCO) for natural-gas flow through two centrifugal-compressor stations with different performances, as in Table 1.

The problem was solved by use of a genetic algorithm and the software program Lingo (Thompson 2011) to compare the results of optimization. Lingo is a comprehensive tool designed for building and solving nonlinear optimization models.

Tables 2 and 3 and Figs. 6 and 7 show the results for Stations 1 and 2 before and after the optimization process. In Table 2 for Station 1, the optimum speeds of Compressors 1, 2, and 3 obtained from the genetic algorithm are 205.14, 188.62, and 179.3 rev/sec, respectively, while the decreasing rate between the speeds of the compressors before optimization and after optimization are 2.892, 2.577, and 0.994%, respectively. On the other hand, the optimum speeds of the compressors obtained from Lingo are 207.16, 189.02, and 180.3 rev/sec, while the decreasing rates between the speeds of the compressors before and after optimization are 1.936, 2.370, and 0.441%, respectively.

Table 3 shows the results for Station 2 before and after the optimization process. We can notice that the optimum speeds of Compressors 1, 2, and 3 obtained from the genetic algorithm are 205, 187, and 179.05 rev/sec, respectively, while the decreasing rates between the compressor speeds before and after optimization are 2.958, 3.414, and 1.132%, respectively. On the other hand, the optimum speeds of the compressors obtained with Lingo are 209.13, 186.9, and 179.81 rev/sec, respectively, while the decreasing rates between the speed of the compressors before and after optimization are 1.003, 3.465, and 0.712%.

From the previous results, the case study clearly indicates the effectiveness and ease of use in the actual application of the developed and implemented genetic-algorithm methodology.

Table 4 shows that the mass-flow rate is 369.45 lbm/sec before optimization, 362.37 lbm/sec after optimization with the genetic algorithm, and 363.92 lbm/sec after optimization with Lingo. The fuel consumption is 18.3 lbm/sec before optimization, 17.011 lbm/sec after optimization with genetic algorithm, and 17.231 lbm/sec after optimization with Lingo. From these results, the model was further applied to two cases and the best operational points with the minimum rate of fuel consumption were established for a centrifugal-compressor station.

<table>
<thead>
<tr>
<th>Items</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative density</td>
<td>0.6</td>
</tr>
<tr>
<td>Molecular weight in lbm/lbm-mol at 125.6°F</td>
<td>17,382</td>
</tr>
<tr>
<td>Pressure (lb/ft²)</td>
<td>129,105</td>
</tr>
<tr>
<td>Relative roughness (in.)</td>
<td>0.0007</td>
</tr>
<tr>
<td>Minimum-speed operation of compressor (rev/sec)</td>
<td>150</td>
</tr>
<tr>
<td>Maximum-speed operation of compressor (rev/sec)</td>
<td>235</td>
</tr>
<tr>
<td>Discharge pressure (lb/ft²)</td>
<td>106,237</td>
</tr>
<tr>
<td>Mass-flow rate (lbm/sec)</td>
<td>370.38</td>
</tr>
<tr>
<td>Pipe diameter (in.)</td>
<td>24</td>
</tr>
</tbody>
</table>

Table 1—Data given for natural-gas flow through two compressor stations.
Conclusions

1. Using modular programming techniques and genetic algorithm, the operational optimized points in fuel consumption were generated.

2. The flexibility of genetic algorithm enables it to perform various assessments for a given problem and optimize the problem according to the formulation of the objective function.

3. The case study clearly indicates the effectiveness and ease of use in the actual application of the developed and implemented methodology.

4. The model was further applied to two case studies, and the best operational points with the minimum rate of fuel consumption were established for a typical compressor station.

Table 2—The results for Station 1 before and after the optimization process.

<table>
<thead>
<tr>
<th>Compressor</th>
<th>Before Optimization</th>
<th>After Optimization With Genetic Algorithm</th>
<th>After Optimization With Lingo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed</td>
<td>211.25 rev/sec</td>
<td>205.14 rev/sec (2.892%)</td>
<td>207.16 rev/sec (1.936%)</td>
</tr>
<tr>
<td>Efficiency</td>
<td>81.21</td>
<td>81.01 (0.246%)</td>
<td>79.2 (2.475%)</td>
</tr>
<tr>
<td>Speed</td>
<td>193.61 rev/sec</td>
<td>188.62 rev/sec (2.577%)</td>
<td>189.02 rev/sec (2.370%)</td>
</tr>
<tr>
<td>Efficiency</td>
<td>79.51</td>
<td>79.24 (0.341%)</td>
<td>79.1 (0.515%)</td>
</tr>
<tr>
<td>Speed</td>
<td>181.1 rev/sec</td>
<td>179.3 rev/sec (0.994%)</td>
<td>180.3 rev/sec (0.441%)</td>
</tr>
<tr>
<td>Efficiency</td>
<td>78.31</td>
<td>78.29 (0.026%)</td>
<td>77.94 (0.472%)</td>
</tr>
</tbody>
</table>

Table 3—The results for Station 2 before and after the optimization process.

<table>
<thead>
<tr>
<th>Compressor</th>
<th>Before Optimization</th>
<th>After Optimization With Genetic Algorithm</th>
<th>After Optimization With Lingo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed</td>
<td>211.25 rev/sec</td>
<td>205 rev/sec (2.958%)</td>
<td>209.13 rev/sec (1.003%)</td>
</tr>
<tr>
<td>Efficiency</td>
<td>81.21</td>
<td>80.89 (0.394%)</td>
<td>80.01 (1.478%)</td>
</tr>
<tr>
<td>Speed</td>
<td>193.61 rev/sec</td>
<td>187 rev/sec (3.414%)</td>
<td>186.9 rev/sec (3.465%)</td>
</tr>
<tr>
<td>Efficiency</td>
<td>79.51</td>
<td>79.34 (0.214%)</td>
<td>79.4 (0.214%)</td>
</tr>
<tr>
<td>Speed</td>
<td>181.1 rev/sec</td>
<td>179.05 rev/sec (1.132%)</td>
<td>179.81 rev/sec (0.712%)</td>
</tr>
<tr>
<td>Efficiency</td>
<td>78.31</td>
<td>78.17 (0.179%)</td>
<td>77.96 (0.447%)</td>
</tr>
</tbody>
</table>

Table 4—The results for mass-flow rate and fuel consumption before and after the optimization process.

<table>
<thead>
<tr>
<th>Items</th>
<th>Before Optimization</th>
<th>After Optimization With Genetic Algorithm</th>
<th>After Optimization With Lingo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mass-flow rate</td>
<td>369.45</td>
<td>362.37</td>
<td>363.921</td>
</tr>
<tr>
<td>(lbm/sec)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fuel consumption</td>
<td>18.30</td>
<td>17.011</td>
<td>17.231</td>
</tr>
<tr>
<td>(lbm/sec)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 6—Results of compressor speed before and after the optimization process for Station 1.
Nomenclature
Note that $a$, $A$, $A_E$, $A_R$, $b$, $B$, $B_E$, $B_R$, $C$, $C_E$, $C_R$, $D$, $D_E$, $D_R$, $Z_0$, $Z_1$, $Z_2$, $Z_3$, and $Z_4$ are constants.

$AL$ = auxiliary load, ft-lbf/sec
$APWR$ = available power, ft-lbf/sec
$ARF$ = ambient rating factor, °R
$FAP$ = fraction of available power, [-]
$FC$ = fuel consumption, scf/sec, [std m$^3$/s]
$H$ = adiabatic head, ft-lbf/lbm
$HV$ = heating value, ft-lbf/lbm
$j$ = the response, rev/sec
$k$ = specific heat ratio, [-]
$n$ = number of bits, [-]
$p$ = pressure, psia
$P_c$ = pseudocritical pressure, psia
$P_d$ = discharge pressure, psia
$P_s$ = suction pressure, psia
$PWR$ = required power of the compressor, ft-lbf/sec
$q$ = flow rate, ft$^3$/sec
$q_i$ = inlet volumetric flow rate, ft$^3$/sec
$R$ = gas constant, ft$^3$-psi/(lbm mol-°R).
$RPWR$ = rated power, ft-lbf/sec
$s$ = speed, rev/sec
$s_i$ = speed of the ith compressor available in the station, rev/sec
$T_A$ = ambient temperature, °R
$T_c$ = pseudocritical temperature, °R
$T_R$ = rated temperature, °R
$W$ = mass-flow rate, slug/sec
$Y_{S1}$ = constant = 0.42748
$Y_{S2}$ = constant = 0.866403
$Z$ = gas-compressibility factor, [-]
$\eta$ = efficiency, [-]
$\eta_D$ = driver efficiency, [-]
$\eta_{mech}$ = mechanical efficiency, [-]

References


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