Optimization of Fuel Consumption in Compressor Stations

T.M. Elshiekh, Egyptian Petroleum Research Institute

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 Ríos-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.

Edgar and Himmelblau (1988) and Osiadacz (1994) used both nonlinear programming (NLP) and a branch-and-bound scheme for optimal design of gas-transmission systems. Wolf and Smeers (2000) used mixed-integer NLP (MINLP) for fuel-cost minimization. Kabirian and Hemmati (2007) applied an integrated nonlinear-optimization model and a heuristic random-search method for design and development of natural-gas-transmission pipeline networks. Chebouba et al. (2009) applied ant-colony optimization (ACO) for the first time for the fuel-consumption-minimization problem in natural-gas-transportation systems. For gas-pipeline-operation optimization, the ACO algorithm is a new evolutionary optimization method. Zhang et al. (2009) applied a fuzzy optimization for design of a gas pipeline.

Goslinga 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). Tsal 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 Behbahani (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 Kralik (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

Original SPE manuscript received for review 17 February 2014. Revised manuscript received for review 28 September 2014. Paper (SPE 173888) peer approved 14 October 2014.

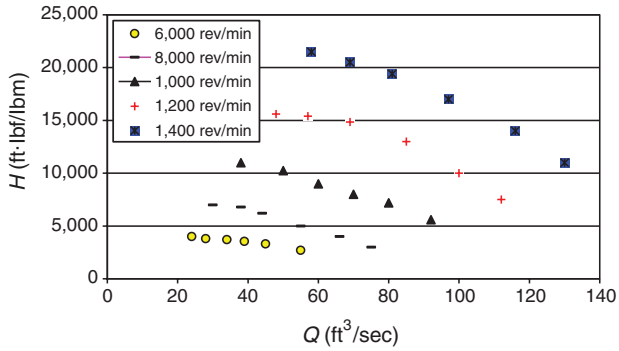

Fig. 1—Single-centrifugal-compressor map.

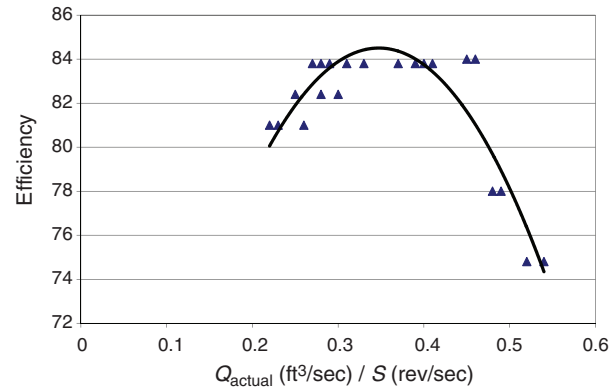

Fig. 2—Compressor efficiency as a function of Q_{actual} per speed.

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 studied.

Problem Formulation

Centrifugal Compressor. Habibvand and Behbahani (2012) showed that the governing quantities of a centrifugal compressor unit are inlet volumetric flow rate Q_i, speed S (rev/sec), adiabatic head H (ft-lbf/lbm), and adiabatic efficiency η. 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 η.

Figs. 1 and 2 show the set of data collected from a typical centrifugal unit. Fig. 1 represents H_i (ft-lbf/lbm) vs. Q_i (ft^3/sec) at different speed values for S_i (rev/sec) (between $S_{i,\min}$ and $S_{i,\max}$ in rev/sec) and Q_i/S_i generated by Eq. 1. 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

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

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

$$PWR = \frac{32.174 \times W \times H}{\eta \times \eta_{\text{mech}}} + Al. \quad \text{.....(4)}$$

Centrifugal compressors have been bounded within choke/stonewall 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

$$Z = Z_0 + \left(Z_1B + Z_2A^2\right)P + \left(3Z_3BA^2 + Z_4A^4\right)P^2. \quad \text{.....(6)}$$

A and B are constants that depend on the gas temperature and the pseudocritical pressure and temperature. The constants a and b are $a = Z_1B + Z_2A^2$ and $b = 3Z_3BA^2 + Z_4A^4$. The values of A and B are $A^2 = VS_1T_C^{2.5}/P_CT^{2.5}$ and $B = VS_2T_C/P_CT$.

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

$$APWR = \left[1 - ARF\left(T_A - T_R\right)\right] \times RPWR\,, \quad (7)$$

$$FAP = \frac{PWR}{APWR}\,, \quad (8)$$

and

$$FC = PWR \big/ \left(\eta_D \times HV\right)\,. \quad (9)$$

Optimization

Objective Function. Dual-shaft gas turbines are used as drivers. When centrifugal compressors are driven by gas turbines, they may initiate diverse operational circumstances through velocity control. This is one of the most natural manners of controlling the transmission system because the centrifugal compressor and dual-shaft gas turbines can function on a wide range of velocities. Having determined the flow rate by means of a tool such as an orifice, by a Venturi nozzle, or by infrasonic equipment, the controller can alter the fuel flow in case any change in the output or input pressure transpires. Thus, the gas turbine will produce energy commensurate with the consumed fuel and will instigate the decrease of the compressor rotation. Hence, it is quite worthy to opt for the compressor rotation velocity as a decision-making variable. The consumption rate of the gas-turbine fuel relation can be applied to determine the target function, thus counterpoising the power initiated in the gas turbine with the required energy to materialize the set points and constraints of the compressor and transmission system. The relationship can be simplified on the basis of the decision-making variable.

$$\min \sum_{i=1}^{n} FC\left(S_i\right) = \min \sum_{i=1}^{n} \frac{PWR_i}{\eta_{Di} \times HV}\,. \quad (10)$$

Constraints. The constraints are usually provided. They are minimum speed $S_{i,\min}$ (rev/sec), maximum speed $S_{i,\max}$ (rev/sec), surge-limit surge, and stonewall-limit stonewall. These provide the limits to the speed S_i and the ratio of Q/S:

$$S_{i,\min} \le S_i \le S_{i,\max} \quad (11)$$

and

$$surge \le \frac{Q_i}{S_i} \le stonewall\,. \quad (12)$$

From Eqs. 11 and 12, it follows that the inlet volumetric flow rate Q_i (ft^3/sec) must satisfy conditions, where $Q_i^L = S_{i,\min} \times surge$ and $Q_i^U = S_{i,\max} \times stonewall$. For each Q_i within this range, the adiabatic head H_i is bounded below by either $S_{i,\min}$ or stonewall and bounded above by either $S_{i,\max}$ or surge. Let $H_i^L\left(Q_i\right)$ and $H_i^U\left(Q_i\right)$ be the lower and upper bound functions, respectively. Then,

$$H_i^L\left(Q_i\right) \le H_i \le H_i^U\left(Q_i\right),\ Q_i^L \le Q_i \le Q_i^U\,. \quad (13)$$

Genetic Algorithm. Quindry et al. (1981) and Murphy and Simpson (1992) used genetic algorithms, which are intended for use in problems involving complex spaces. The idea is similar to the evolution principle stated by Darwin and based on species reproduction and survival. Genetic algorithms start with a population of initial solutions to a certain problem and evolve them toward the best solution. Generation by generation, this population is evolved in such a way that the best solutions win over the worst solutions, as in natural evolution. Malhotra et al. (2011) discuss the concept and design procedure of the genetic algorithm as an optimization tool for process-control applications. Genetic algorithms are applied to the speed control of gas turbines as well as other control parameters. Habibvand and Behbahani (2012) demonstrated the use of a genetic algorithm for fuel-consumption optimization of a natural-gas-transmission compressor station. They demonstrated that genetic algorithms are computationally more demanding than conventional optimization algorithms, but offer many advantages over conventional methods. Goldberg (1989) shows that a genetic algorithm is different from more-traditional optimization techniques in four important ways:

- 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 transfigure 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.

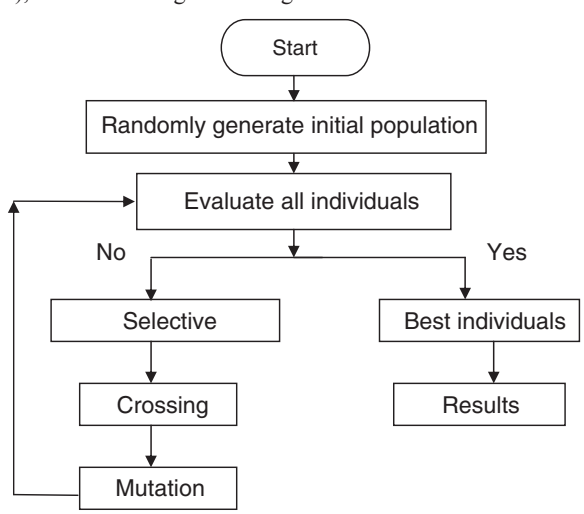

Fig. 3—Genetic-algorithm-optimization procedure.

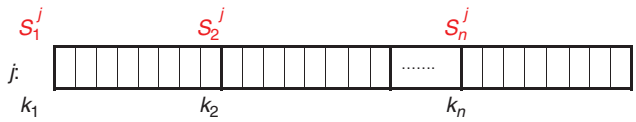

Fig. 4—Shape of each chromosome.

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.

$$j = \left\{ s_1^j, s_2^j, \ldots\ldots\ldots\ldots, s_n^j \right\} . \quad (14)$$

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.

$$s_i^L < s_i < s_i^U , \quad (15)$$

$$Sd_i = S_{i,\max} - S_{i,\min} , \quad (16)$$

and

$$Sd_i < 2^{k_i} . \quad (17)$$

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:

$$s_i = s_i^L + \frac{Sd_i}{n \times k_i} . \quad (18)$$

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.**

Items	Value
Relative density	0.6
Molecular weight in lbm/lbm·mol at 125.6°F	17.382
Pressure (lbf/ft^2)	129,105
Relative roughness (in.)	0.0007
Minimum-speed operation of compressor (rev/sec)	150
Maximum-speed operation of compressor (rev/sec)	235
Discharge pressure (lbf/ft^2)	106,237
Mass-flow rate (lbm/sec)	370.38
Pipe diameter (in.)	24

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

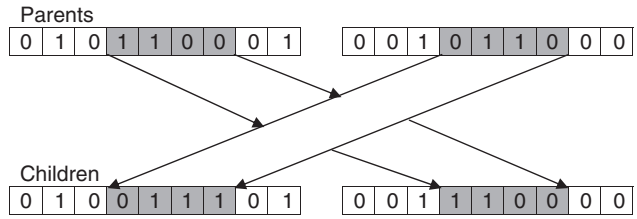

Fig. 5—Crossover two-point cut operator.

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 speed 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 compressor speeds 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 363.921 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.

Station 1	Before Optimization	After Optimization With Genetic Algorithm		After Optimization With Lingo	
		Optimum Value	Decreasing Rate (%)	Optimum Value	Decreasing Rate (%)
Compressor 1 speed	211.25 rev/sec	205.14 rev/sec	2.892	207.16 rev/sec	1.936
Compressor 1 efficiency	81.21	81.01	0.246	79.2	2.475
Compressor 2 speed	193.61 rev/sec	188.62 rev/sec	2.577	189.02 rev/sec	2.370
Compressor 2 efficiency	79.51	79.24	0.341	79.1	0.515
Compressor 3 speed	181.1 rev/sec	179.3 rev/sec	0.994	180.3 rev/sec	0.441
Compressor 3 efficiency	78.31	78.29	0.026	77.94	0.472

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

Station 2	Before Optimization	After Optimization With Genetic Algorithm		After Optimization With Lingo	
		Optimum Value	Decreasing Rate (%)	Optimum Value	Decreasing Rate (%)
Compressor 1 speed	211.25 rev/sec	205 rev/sec	2.958	209.13 rev/sec	1.003
Compressor 1 efficiency	81.21	80.89	0.394	80.01	1.478
Compressor 2 speed	193.61 rev/sec	187 rev/sec	3.414	186.9 rev/sec	3.465
Compressor 2 efficiency	79.51	79.34	0.214	79.4	0.214
Compressor 3 speed	181.1 rev/sec	179.05 rev/sec	1.132	179.81 rev/sec	0.712
Compressor 3 efficiency	78.31	78.17	0.179	77.96	0.447

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

Items	Before Optimization	After Optimization With Genetic Algorithm	After Optimization With Lingo
Mass-flow rate (lbm/sec)	369.45	362.37	363.921
Fuel consumption (lbm/sec)	18.30	17.011	17.231

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

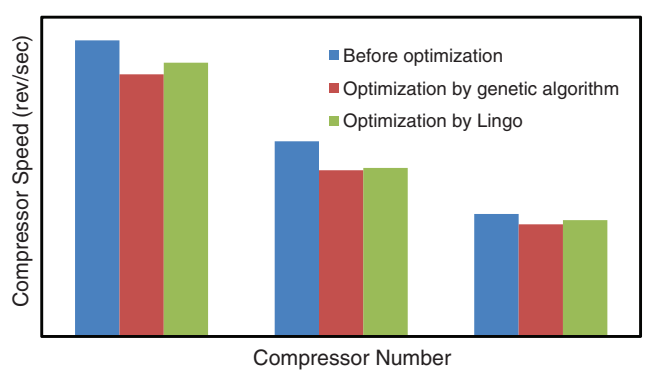

Fig. 6—Results of compressor speed before and after the optimization process for Station 1.

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.

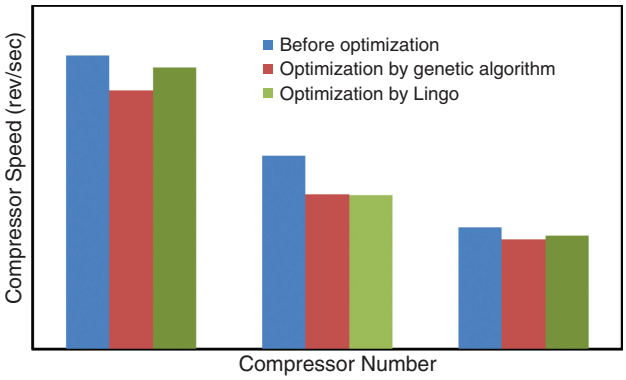

Fig. 7—Results of compressor speed before and after the optimization process for Station 2.

Nomenclature

Note that a, A, A_E, A_H, b, B, B_E, B_H, C_E, C_H, D_E, D_H, 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/scf
j = the response, rev/sec
k = specific heat ratio, [–]
$\mathbf{k}$ = number of bits, [–]
n = population size, [–]
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
Sd = difference of the velocity, 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
VS_1 = constant = 0.42748
VS_2 = constant = 0.0866403
Z = gas-compressibility factor, [–]
η = efficiency, [–]
η_D = driver efficiency, [–]
η_{mech} = mechanical efficiency, [–]

References

Andrus, S.J. 1994. Steady State Simulation of Pipeline Networks Using a Spreadsheet Model. Presented at the PSIG Annual Meeting, San Diego, California, 13–14, October. PSIG-9401.

Borraz-Sánchez, C. 2010. Minimizing Fuel Cost in Gas Transmission Networks by Dynamic Programming and Adaptive Discretization. *Journal of Computers & Industrial Engineering* **61** (2): 364–372. http://dx.doi.org/10.1016/j.cie.2010.07.012.

Cameron, I. 1999. Using an Excel-Based Model for Steady-State and Transient Simulation. Presented at the 31st PSIG conference, St. Louis, Missouri, 20–22, October.

Chapman, K.S. and Abbaspour, M. 2003. Non-isothermal Compressor Station Transient Modeling. Presented at the PSIG Annual Meeting, Bern, Switzerland, 15–17 October. PSIG-03A3.

Chebouba, A., Yalaoui, F., Smati, A. et al. 2009. Optimization of Natural Gas Transmission Pipelines using Ant Colony Optimization. *Computers & Operations Research* **36** (6): 1916–1923. http://dx.doi.org/10.1016/j.cor.2008.06.005.

Edgar, T.F. and Himmelblau, D.M. 1988. Optimal Design of Gas Transmission Networks. *SPE J.* **18** (2): 96–104. SPE-6034-PA. http://dx.doi.org/10.2118/6034-PA.

Flores-Villarreal, H.J. and Ríos-Mercado, R.Z. 2003. Efficient Operation of Natural Gas Pipeline Networks: Computational Finding of High Quality Solutions. Presented at the International Applied Business Research Conference, Acapulco, Mexico.

Goldberg, D.E. 1989. *Genetic Algorithms in Search, Optimization, and Machine Learning,* first edition. Boston, Massachusetts: Addison-Wesley Longman Publishing Company.

Goldberg, D.E. and Kuo, C.H. 1985. Genetic Algorithms in Pipeline Optimization. Presented at the PSIG Annual Meeting, Albuquerque, New Mexico, 24–25 October. PSIG-8506.

Goslinga, J., Kaulback, M., Witczak, K. et al. 1994. A Method for Pipeline Network Optimization. *Proc.,* the 13th International Conference on Offshore Mechanics and Arctic Engineering, Volume V: 31–43.

Habibvand, G. and Behbahani, R.M. 2012. Using Genetic Algorithm for Fuel Consumption Optimization of a Natural Gas Transmission Compressor Station. *International Journal of Computer Applications* **43** (1): 1–6. http://dx.doi.org/10.5120/6064-8180.

Hawryluk, A., Botros, K.K., Golshan, H. et al. 2010. Multi-Objective Optimization of Natural Gas Compression Power Train with Genetic Algorithms. Presented at the 8th International Pipeline Conference, Calgary, 27 September–1 October. IPC2010-31017. http://dx.doi.org/10.1115/IPC2010-31017.

Jenicek, T. and Kralik, J. 1995. Optimized Control of Generalized Compressor Station. Presented at the PSIG Annual Meeting, Albuquerque, New Mexico, 18–20 October. PSIG-9502.

Jin, L. and Wojtanowicz, A.K. 2010. Optimization of Large Gas Pipeline Network—A Case Study in China. *J Can Pet Technol* **49** (4): 36–43. SPE-136345—PA. http://dx.doi.org/10.2118/136345-PA.

Kabirian, A. and Hemmati, M.R. 2007. A Strategic Planning Model for Natural Gas Transmission Networks. *Energy Policy* **35** (11): 556–5670. http://dx.doi.org/10.1016/j.enpol.2007.05.022.

Malhotra, R., Singh, N., and Singh, Y. 2011. Genetic Algorithms: Concepts, Design for Optimization of Process Controllers. *Computer and Information Science* **4** (2): 39–54. http://dx.doi.org/10.5539/cis.v4n2p39.

Mallinson, J.R., Meilton, S.P., Revell, N.J. et al. 1986. Falcon User Manual Part I - Falcon Overview. Report No. LRS, British Gas, London Research Station, Adrian Robinson Publication Services, London, SW6 2AD, 9/1986.

More, J.J. and Wright, S.J. 1993. Optimization Software Guide. In *Frontiers in Applied Mathematics*. Philadelphia, Pennsylvania: Society for Industrial and Applied Mathematics. http://dx.doi.org/10.1137/1.9781611970951.

Murphy, L.J. and Simpson, A.R. 1992. Genetic Algorithm in Pipe Network Optimisation. Research Report No. R93, Department of Civil and Environment Engineering, University of Adelaid, Adelaid, Australia (June 1992).

Odom, F. and Muster, G.L. 1991. Tutorial on Modeling Gas Turbine Driven Centrifugal Compressors. PSIG Annual Meeting, Galveston, Texas, 12–15 May. PSIG-09A4.

Osiadacz, A.J. 1994. Dynamic Optimization of High Pressure Gas Networks Using Hierarchical Systems Theory. PISG Annual Meeting, San Diego, California, 13–14 October. PSIG-9408.

Quindry, G.E., Liebman, J.C., and Brill, E.D. 1981. Optimization of Looped Water Distribution System. *Journal of Environmental Engineering Division* **107** (4): 665–679.

Thompson, J.H. 2011. *Lingo*, version 13.0.2.17. Chicago, Illinois: LINDO Systems Inc.

Tsal, R.J., Gordon, E., Simpson, K.O. et al. 1986. Optimal Gas Pipeline Design Via Dynamic Programming with Variable Stages. Presented

at the PISG Annual Meeting, New Orleans, 30–31 October. PSIG-8601.

Woldeyohannes, A.D. and Majid, M.A.A. 2011. Simulation Model for Natural Gas Transmission Pipeline Network System. *Simulation Modelling Practice and Theory* **19** (1): 196–212. http://dx.doi.org/10.1016/j.simpat.2010.06.006.

Wolf, D.D. and Smeers, Y. 2000. The Gas Transmission Problem Solved by an Extension of the Simplex Algorithm. *Management Science* **46** (11): 1454–1465. http://dx.doi.org/10.1287/mnsc.46.11.1454.12087.

Wright, S., Ditzel, C., and Somani, M. 1998. Compressor Station Optimization. Presented at the PSIG Annual Meeting, Denver, 28–30 October. PSIG-9805.

Zhang, Q., Chen, N., and Luo, J. 2009. Fuzzy Optimization Design of Gas Pipeline. In *Fuzzy Info. and Eng.*, Vol. 2, AISC 62, 1201–1208. http://dx.doi.org/10.1007/978-3-642-03664-4_128.

T.M. Elshiekh is associate professor and head of the Energy Laboratory Process Design and Development Department within the Egyptian Petroleum Research Institute (EPRI). He joined the EPRI in 1990 and worked in the field of simulation and optimization in oil and gas pipelines and energy savings. Elshiekh has published several papers in international journals on these topics. He holds MSc and PhD degrees in mechanical power engineering from Menoufiya University, Egypt.