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# Optimization of Natural Gas Pipeline Design and Its Total Cost Using GA

**Ram Ratan Singh[1], P K S Nain[2]**

[1] Pipeline & Projects Department, Hindustandan Petroleum Corporation Ltd, Mumbai
[2] Mechanical Engineering Department Noida Institute of engineering & technology Greater Noida

***Abstract***- We has presented a methodology for the application of genetic algorithm technique to pipeline network optimization. The GA codes the pipe sizes available for selection as binary strings. We have used a simple three-operator genetic algorithm namely reproduction, crossover, and mutation. Results represented to show that the genetic algorithm techniques are very effective in finding near-optimal or optimal solutions for a case study network in relatively few evaluations.

The GA technique generates a whole class of alternatives solutions close to optimum. One of these alternative solutions may actually be preferred to the optimum solution based on non quantifiable measures. This is a major benefit of genetic algorithm method. The genetic algorithms technique is infancy, and further development should provide improvements in these search method for practical problem.

## I. Introduction

Cross-country pipeline transport for Natural Gas (NG) seems to be most preferred convient economical & reliable method. The intrinsic properties of Natural Gas and its increasing industrial/commercial importance have resulted in greater movement of Natural Gas through the pipeline. These pipelines are often referred as highways of Natural Gas transmission. NG is transported at high pressure in the pipeline at pressure anywhere between 30~100 bar. This reduces the volume of Natural Gas being transported, as well as providing propellant force to move the NG through the pipeline.

The term pipeline also implies a relatively large pipe spanning a long distance. Unless otherwise specified, the pipelines have a minimum diameter of 4 inches (102 mm) and a minimum length of 1 mile (1.6 km). The largest and longest pipelines may have a diameter of over 10 ft (3.05 m) and a length of over 1000 miles (1609 Km).

It is well recognized that the natural gas resources in the world's ocean are gaining increasing importance as an energy source to help fuel world economic growth in the established and emerging economies alike. Pipelines carry a special role in the development and production of gas reserves since, at this point in time, they provide one of the most reliable means for transportation given that fewer options are available than for the movement of Natural Gas. Add to this the growing need to provide major transportation infrastructure between gas producing regions and countries wishing to import gas, and future oil transmission systems, then the requirement for new offshore/onshore pipelines appears to be set for several years to come. Even today, plans for pipeline transportation infrastructure are in development for regions with more hostile environments and deeper waters than would have been thought achievable even ten years ago.

The optimization of the design of a gas pipeline to transmit Natural gas involves a number of variables, which include pipe diameter, pressure, temperature, line length, and space between compressor stations, required inlet and delivery pressures and delivery quantity. Each of these parameters influences the overall construction and operating cost in some degree and the selection of one or more will determine the economics of the construction and operation of the system. This is as true for the design of a system from a clean sheet of paper (grass roots) as it is for the development and upgrading of an existing system, the only real difference between these two examples is the extent to which some of the variables are already fixed.

Because of the number of variables involved, the task of establishing the optimum can be quite involved and in order to ensure a robust solution, many options may have to be investigated. Also, all of the "what if" scenarios need to be studied to ensure that no possibilities are overlooked and the future unknowns can be adequately covered. The simulation program which has been developed and which is intended to provide optimum solutions to the design of a pipeline system and to permit the rapid investigation of the effects of significant variables on the optimum design.

## II. Literature Review

### 2.1. Pipeline optimization by computer simulation:

Pipeline designers and pipeline companies have over time developed their own methods for the optimum system design and continue to use these. This program is not intended to supplant some of these tried and true methods, it is intended to show how the process can be accelerated and how the optimum solution can be easily demonstrated, thereby cutting short the long and laborious process of investigating, by "long hand" all the possible options.

An example of an optimization exercise for a "grass roots" system undertaken some years ago required over a man year of work to arrive at the optimum answer which satisfied all the defined scenarios. The program is intended to reduce the time and expense of this procedure by several orders of magnitude. The simulation is an extension of a simple program, which was developed to evaluate the
selection of compressor driver for gas pipelines. It may be helpful to describe this program before discussing the more complex *pipeline model [49]*.

**2.1.1 Selection of Compressor Driver:**

A question that frequently arises for the system designer concerns the selection of a compressor driver. Should a gas turbine, an electric motor or a reciprocating engine drive the compressor, and what will be the owning and operating cost of each option?

The key variables in this study are the capital costs, the maintenance costs, the fuel or energy costs, the utilization and the overall efficiency of each option. Combining these in a simple model allows the designer to show the overall cost of each on an annual and a total life of project cost basis. In addition to this, the program permits a number of sensitivity studies to be carried out, demonstrating the effect of changes in cost of fuel and utilization, for example. This program has been successfully employed in a number of feasibility studies to demonstrate to clients the possible choices within the constraints of operating variables such as energy costs and utilization.

An example of the application of this program is a comparison between an existing electrically driven compressor on a pipeline and the possibility of its replacement by a gas turbine. The question of replacement of the driver arose because of a projected increase in utility rates.

The use of the program permitted a very rapid review of the consequences of changes in the power costs and a graphical.

**2.1.2 The Pipeline Program:**

The foregoing compressor program has relatively few variable parameters; the pipeline case has considerably more and involves a greater degree of calculation. The principal variables for a pipeline and the dependent parameters can be listed as follows: Maximum pressure, limits of pipe stress, affecting pipe thickness and pipe cost; Throughput, affecting pipe diameter, compressor (pump) horsepower and cost; Compressor station spacing, affecting compressor (pump) horsepower and cost; Delivery pressure limits; Line length.

The cost elements include not only material cost but also construction cost, operating cost and maintenance, fuel or energy cost and represent the life cycle cost of the project.

A general definition is the transport of a volume of gas “Q” from point “A” to point “B” over a distance of "X" km. A typical case for a green fields pipeline project would specify the throughput and the length of the line from reception point to delivery and the limiting pressure at delivery. The evaluation would then examine the impact of pipe stress limit and maximum pressure, variations in pipe diameters, compressor station spacing and horsepower, from which a set of “J” curves can be produced.

The depiction of these relationships in a 2-dimensional form requires a number of different screens, each one of which can demonstrate an optimum point, assuming for example that least capital cost or the least oweing an operating cost are the desiredends.

The simulation program provides outputs in the form of Tables, which provide data on all parameters influencing the design of the pipeline. Since the number of variables is large when a new pipeline design is being considered, several screens are incorporated in the output.

However the ultimate objective is a series of Jcurves which will, in combination, show the influence of changes in the key variables. The optimum pipeline system may be presumed to be the system, which, within the prescri limits, will provide the lowest or most economic cost of transportation for the quantity of fluid.

**2.1.3 The Pipe Track Program:**

The development of the pipe track program follows the pattern of the Compressor driver program, using established pipeline data and formulae and compressor data and formulae. The first element comprises the hydraulic analysis which is based upon the use of one or other of the well known fluid flow formulae, in the examples used, the modified Panhandle has been incorporated. This permits the relation between throughput and pipe size and compression power to be established. One of the key parameters and the basis for design will be the maximum operating pressure. Selection of maximum pressure for the system and the throughput required the effect of compressor station spacing and pipe diameter could be demonstrated.

With the hydraulic calculations set up in terms of maximum pressure, throughput and pipe size, the compressor power can be found as a function of station spacing, and following this process compressor capital and operating cost can be established, given assumptions on fuel or energy cost and escalation. The calculation process includes all cost elements as well as the hydraulics, stress and thermodynamic performance elements.Any combination of key parameters can be used to explore the effect of changes in the others to show the impact on overall cost.

**2.1.4 Cost:**

The cost elements include all of the above physical parameters: Cost of material, pipe, cost of compressors, cost of fuel and energy, cost of construction, cost of operation, (fuel maintenance; utilization), total life cycle cost, etc.

The cost of each and every set of variations can be tabulated on a year by year basis and the total cost over the project life compared.

Costs are backed up with an extensive database of all the cost components and the performance of compression units based on latest published information.

The cost components can be varied to include changes as a result of new technology. For example, high-speed electric drive for compressors, new construction techniques, etc.

The program is not limited to the evaluation within the above defined problem limits but may be extended to examine the impact of a change in quantity to be delivered on the overall economics as would be the case of expansion of an existing system. It also could influence the initial design of a new system to study the possible effects of future, additional supplies being brought on stream.

**2.2 Pipeline optimization using differential Evolution:**

Differential Evolution (DE), an evolutionary computation technique *[31]*, is applied for the optimal design of gas pipeline transmission network in this study. The design of an efficient and economical network involves many parameters in a gas transmission system such as source of gas, delivery sites with pipeline segments and compressors, etc. In addition, there are many equality and inequality constraints to be satisfied making the problem highly complex. Hence an efficient strategy is needed in searching for the global optimum. DE has been successfully applied for this complex and highly non-linear problem. The results obtained are compared with those of nonlinear programming technique and branch and bound algorithm. DE is able to find an optimal solution satisfying all the constraints. The proposed strategy takes less computational time to converge when compared to the existing techniques without compromising with the accuracy of the parameter estimates.

In this age of high competition in the several industries, it becomes necessary to cut down capital and operating costs as much as possible. Specifically in case of Chemical industries, the main focus is on reducing the processing costs, which include heating, cooling, transfer of various streams involved in any operational unit. The gas transmission network, which forms a considerable fraction of the operating cost, is also one of the focus areas. Broadly, a gas transmission system includes source of gas, delivery sites with the pipeline segments and compressor stations used to achieve desired pressure at the delivery site. As the design of an efficient and economical gas transmission network involves a lot of design parameters which directly/indirectly affect the capital and operating costs, this topic deserves special attention. Over the years, various aspects of the problem have been addressed *[18-25]*. *Larson and Wong [18]* determined the steady state optimal operating conditions of a straight natural pipeline with compressors in series using dynamic programming to find the optimal suction and discharge pressures. The length and diameter of the pipeline segment were assumed to be constant because of limitations of dynamic programming. *Martch and McCall [20]* modified the problem by adding branches to the pipeline segments. However, the transmission network was predetermined because of the limitations of the optimization technique used. *Cheesman [23]* introduced a computer optimizing code in addition to *Martch and McCall [20]* problem. They considered the length and diameters of the pipeline segments to be variables. But their problem formulation did not allow unbranched network, so complicated network systems couldn't be handled. *Olorunniwo [40]* and *Olorunniwo and Jensen [26]* provided further breakthrough by optimizing a gas transmission network including the following features:

1. The maximum number of compressor stations that would ever be required during the specified time horizon.
2. The optimal location of these compressor stations.
3. The initial construction dates of the stations.
4. The optimal solutions of expansion for the compressor stations.
5. The optimal diameter sizes of the main pipes for each arc of the network.
6. The minimum recommended thickness of the main pipe.
7. The optimal diameter sizes, thicknesses and lengths of any required parallel pipe loops on each arc of the network.
8. The timing of construction of the parallel pipe loops
9. The operating pressures of the compressors and the gas in the pipelines.

They used dynamic programming coupled with optimization logic to find the shortest route through the network. *Edgar & Himmelblau [27]* simplified the problem to make sure that the various factors involved in the design are clear. They assumed the gas quantity to be transferred along with the suction and discharge pressures to be given in the problem statement. They optimized the following variables:

1. The number of compressor stations
2. The length of pipeline segments between the compressors stations
3. The diameters of the pipeline segments
4. The suction and discharge pressures at each statio

They considered the minimization of the total cost of operation per year including the capital cost in their objective function against which the above parameters are to be optimized. *Edgar and Himmelblau [27]* also considered two possible scenarios:

1. The capital cost of the compressor stations is linear function of the horse power
2. The capital cost of the compressor stations is linear function of the horsepower with a fixed capital outlay for zero horsepower.

The first scenario is easy to solve as compared to the second one. They solved the second scenario using the branch and bound technique.

## III. PROBLEM STATEMENT OF OPTIMIZATION

### 3.1 Problem Formulation:

The pipeline configuration is same as chosen by *Edgar and Himmelblau [27]*. Each of the compressor stations is represented by a node and each of the pipeline segments by an arc. Pressure is assumed to be increasing at a compressor and decreasing along the pipeline segment. The transmission system is presumed to be horizontal. This is a simple example chosen to illustrate a gas transmission system.However, a much more complicated network of pipeline can be accommodated including various branches and loops at the cost of additional execution time.

*Edgar and Himmelblau [27]* distinguished between two related problems (one is of a higher degree of difficulty than the other) before proceeding ahead with the details of the design problem. If the capital costs of the compressors are linear functions of horsepower, then the transmission line problem can be solved as a nonlinear programming problem by one of the methods discussed by *Edgar and Himmelblau [27]*.

Alternately, if the capital costs are a linear function of horsepower with a fixed capital outlay for zero horsepower, a condition that is more closely represents the practical problems, then the design problem becomes more difficult to solve and a branch-and-bound algorithm combined with a nonlinear programming algorithm has to be used.

### 3.2 Number of Variables:

Each node and each arc are labelled separately for a given pipeline configuration. The number of variables is as following:

- Total Compressors : $N$
- Suction Pressures : $N$-1
- Discharge Pressures : $N$

- Pipeline Lengths & Diameters : $N+1$

### 3.3 Variables:

Each pipeline segments has the following variables associated with it:

1. Flow rate
2. Initial pressure
3. Outlet pressure
4. Pipe diameter
5. Pipeline segment length

As the mass flow rate is fixed, only the last four variables become important and need to be determined for each segment in the present problem.

### 3.4 Assumptions:

The following assumptions are made:

1. Each compressor functions adiabatically with an inlet temperature equal to that of the surroundings.
2. Pipeline segment is long so that by the time gas reaches the next compressor it returns to the ambient temperature.
3. The annualized capital costs for each pipeline segment depend on pipe diameter and length, and have been taken as \$870/(inch)(mile)(year) as reported by *Martch and McCall [20]*.
4. The rate of work of one compressor is estimated using the following correlation:

$$W = (0.08531)\ Q^{\frac{k}{k-1}} T_1\left[\left(\frac{pd}{ps}\right)^{z(k-1)/k} -1\right]$$

Where

$k = C_p/C_v$ for gas at suction conditions = 1.26 [28]
$z$ = compressibility factor of gas at suction conditions
$p_s$ = suction pressure, psia
$p_d$ = discharge pressure, psia
$T_1$ = suction temperature = $520^0$R
$Q$ = flow rate into the compressor, MMSCFD (million standard cubic feet per day)
$W$ = rate of work, horsepower

5. the cost is a linear function of horsepower with a fixed initial capital outlay (\$70.00/(hp)(year) + \$10,000), which takes the installation costs, foundation, etc. into account

### 3.5 Objective Function:

As the objective in this study is to **minimize the cost**, the objective function comprises of the sum of the yearly operating and maintenance costs of the compressors in addition to the sum of the discounted capital costs of the pipeline segments and compressors.

$$f = \sum_{i=1}^{n} \left[Cc + \left\{Co\ (0.08531)\ Q_i^{\frac{k}{k-1}} T_1\left[\left(\frac{pd}{ps}\right)^{z(k-1)/k} -1\right]\right\}\right] + \sum_{i=1}^{m} CsLjDj$$

where,
$n$ = number of compressors in the system
$m$ = number of pipeline segments in the system (= $n$ + 1)
$C_0$ = annual operating cost, \$/(hp)(year)
$C_c$ = compressor capital cost, \$/(hp)(year)
$C_s$ = pipe capital cost, \$/(in)(mile)(year)
$L_j$ = length of pipeline segment $j$, mile
$D_j$ = diameter of pipeline segment $j$, inch

*Edgar and Himmelblau [27]* justified the reason why a branch and bound technique is required to solve the design problem for second scenario along with non-linear programming because of the limitations of non-linear programming. However, GA has the capability of dealing with above complications as it is a population-based search algorithm.

### 3.6 Inequality Constraints:

A constraint is there for operation of each compressor as the discharge pressure is always greater than or equal to the suction pressure:

$$\frac{pdi}{psi} \geq 1 \qquad i = 1,2,\ldots\ldots\ldots\ldots,n$$

and the compressor ratio should not exceed some prespecified maximum limit K

$$\frac{pdi}{psi} \leq K_i \qquad i = 1,2,\ldots\ldots\ldots\ldots,n$$

Also, the upper and lower bound are placed on each of the four variables:

$$p_{di}^{min} \leq p_{di} \leq p_{di}^{max}$$

$$p_{si}^{min} \leq p_{si} \leq p_{si}^{max}$$

$$L_i^{min} \leq L_i \leq L_i^{max}$$

$$D_i^{min} \leq D_i \leq D_i^{max}$$

### 3.7 Equality Constraints:

For the gas transmission network chosen in the problem, there are two classes of equality constraints. First, as the length of the system is fixed, there would be three constraints for two branches as given below:

$$\sum_{j=1}^{N_1-1} Lj + \sum_{j=N_1}^{N_1+N_2} Lj = L_1^*$$

$$\sum_{j=1}^{N_1-1} Lj + \sum_{j=N_1+N_2+1}^{N_1+N_2+N_3+1} Lj = L_2^*$$

$$\sum_{j=1}^{N_1-1} Lj = 110$$

where $L_1$* & $L_2$* represents the length of a branch. Secondly, each pipeline segment must satisfy the Weymouth flow equation *[29]*:

$$Qj = 871\ Dj8/3[(p_d^2\text{-}ps^2)/\ L_j]^{0.5}$$

where $Q_j$ is a fixed number, and $p_d$ & $p_s$ are the discharge pressure & suction pressure at the entrance and exit of the segment respectively.

## IV. COMPUTER SIMULATION

**4.1 Genetic Algorithm:**

A genetic algorithm is a member of class of search algorithms based on artificial evolution *Holland,1975[50]*. GAs simulate mechanisms of population genetics and natural rule of the survival in pursuit of the ideas of adaptation. The GA search, sometimes with the modifications to the simple GA formulation, has been shown to perform efficiently in a number of applications. This efficiency indicates the robustness of the search method that underlies the GA approach and the flexibility of the formulation itself *Goldberg, 1989[35]*.

In recent years a number of researchers have applied the genetic algorithm technique to certain aspects of the design of pipeline system. *Goldberg and Kuo 1987[37]* applied the traditional GA to the optimization of the operation of steady state serial gas pipeline consisting of 10 pipes and 10 compressor stations each containning 4 pump in series. The objective in that study was to minimize power while supplying a specified flow and maintaining allowable pressure. *David and Goulter 1994[51]* used Gas to optimize the layout of the branched rectilinear network, such as rural natural gas or water distribution system. The optimal layout in that case was assumed to be one of least length. The layout solutions were represented by blocks of binary code, and new GA operators of recombination and perturbation were introduce to reduce the number of infeasible solutions created by traditional GA operators of crossover and mutation. *Walters and Lohbeck 1993[52]* studies the case of pipe networks with one demand pattern and no constraints on minimum pipe diameters. They showed that GA effectively converges to near-optimal branched network layouts, as selected from a directed base graph which defines a set of possible layouts. In that study the nodal connectivity within the trial branched network solution was represented by the string of code. Alternative GA coding schemes, including a binary representation and an integer representation, were also investigated in that study. *Walters and Cembrowicz 1993[53]* extended these concepts using linear programming for the optimal selection of pipe sizes for branched pipe networks generated by GA. The combination of Gas, graph theory, and linear programming was found by *Walters and Cembrowicz 1993[53]* to be the basis for an effective search for near optimal branched pipe network design.

**4.1.1 Coded Strings:**

The genetic algorithm requires that the decision variables describing trial solution to the pipeline network design problem be represented by a unique code string of finite length. This coded string is similar to the structure of chromosome of genetic code. Consider a coded string consisting of 21 coded substrings each of 4 binary bits. This code string of 84 binary bits. A selected mapping between the coded substring and the design variables associates the artificial genetic code with pipeline design.

**4.1.2 Fitness of the Coded String:**

The fitness of the code string representing a pipe network design is determined by both the pipe cost and hydraulic performance of pipe network design. The cost of pipe network design is taken as the sum of

1. Material, construction, maintenance, and operation costs
2. Penalty costs (where the minimum pressure requirements are violated).

A steady state hydraulic analysis of the pipeline network design is perform to asses the hydraulic feasibility of the proposed system. This hydraulic analysis involves the prediction of the flows in the pipes and hydraulic heads at the nodes in the pipe network under steady state conditions. The hydraulic analysis method adopted in this study uses the *Newton-Raphson* technique applied to the set of simultaneous nonlinear algebraic equations in terms of the unknown flow corrections around the loops. These are called the loop equations *Epp and Fowler,1970 [54] & Wood and Rayes 1981[55]* demonstrated the reliability of this method.

As hydraulic analysis is required for all new strings during the GA run, this can be computationally intensive. As part of this research, we have implemented sparse matrix techniques to ensure the hydraulic solver is as fast as possible.

**4.2 A simple Genetic Algorithm:**

A brief description of the steps in using simple genetic algorithms for pipe network optimization is repeated here for completeness *Simpson et al.,1993[56]:*

**4.2.1 Generation of initial population:** The GA randomly generates an intial population of coded strings representing strings on pipeline network solution of population size N (typically N= 100 to 1000). Each bit position in the string takes on the value of either 1 or 0. Each of the N strings of random starting population represents a possible combination of pipes sizes and thus represents a different configuration of pipe network.

**4.2.2 Computation of network cost:** The GA considers each of the N strings in the population in turn. It decodes each sub-string into the corresponding pipe size and computes the total material and construction cost. The GA determines the costs of each trail pipe network design in the current population.

**4.2.3 Hydraulic analysis of each network:** A steady state hydraulic network solver computes the heads and discharges under the specified demand patterns for each of the network designs in population. The actual nodal pressures are compared with minimum allowable pressure heads, and any pressure deficits are noted.

**4.2.4 Computation of Penalty cost:** The GA assign a penalty cost for the each demand pattern if the pipe network design does not satisfy the minimum pressure constraints. The pressure violation at the node which the pressure deficit is maximum is used as the basis for computation of the penalty factor k, which is measure of the cost of deficit of one unit of pressure head.

**4.2.5 Computation of total network cost:** The total cost of each network in the current population is taken as the sum of the network cost (step 2) plus the penalty cost ( step 4).

**4.2.6 Computation of the fitnesses:** The fitness of the coded string is taken as some function of the total network cost. The GA computes the fitness for each proposed pipe network cost.The GA compute the fitness for each proposed pipe network in the current population as the inverse of the total network cost from step5. Two other forms of fitness function were tried; however, the use of the intensive was found to be the most effective in GA search.

**4.2.7 Generation of new population using the selection operator:** The GA generates new members of the next generation by a selection scheme. The probability of selection of string i, $p_i$, to go into the next generation of N members using a proportionate selection method is given by

$$p_i = f_i / \sum_{j=1}^{N} f_i \qquad (1)$$

Where fi is the fitness of the string i (determined in step 6)

**4.2.8 The crossover operator:** Crossover is partial exchange of bits between two parent strings to form two offspring strings. Crossover occurs with some specified probability of crossover pc for each pair of parent strings selected in step 7. To perform one-point crossover, a crossover point is randomly selected along the strings. The crossover operator exchanges the bits after the crossover point between the two selected parent strings.

**4.2.9 The mutation operator:** Mutation occurs with some specified probability of mutation pm for each bit in the strings which have undergone crossover. The bitwise complement mutation operator changes the value of the bit to the opposite value (i.e., 0 to 1 or 1 to 0).

**4.2.10 Production of Successive generations:** The use of the three operators described above produces a new generation of pipe network design using step 2 to 9. The GA repeats the process to generate successive generations. The least cost string (e.g., the best 20) are stored and updated as cheaper cost alternatives are generated. Tpyically, A GA will evaluate between 100 and 1000 generations

### 4.3 Real- Coded Gentic Algorithm:

Over the past few years, many researchers have been paying attention to real-coded evolutionary algorithms, particularly for solving real-world optimization problems.

Among numerous studies on development of different recombination operators, blend crossover (BLX), simulated binary crossover (SBX), unimodal normal distribution crossover (UNDX), simplex crossover (SPX) are commonly used. A number of other recombination operators, such as arithmetic crossover, intermediate crossover, extended crossovers are similar to BLX operator. A detailed study of many such operators can be found elsewhere *(Deb, 2001[57]; Herrera et al, 1998[58]).* In the recent past, GAs with some of these recombination operators have been demonstrated to exhibit self-adaptive behaviour similar to that in evolution strategy (ES) and evolutionary programming approaches.

*Beyer and Deb (2001)[59]* argued that a recombination operator may have the following two properties:

1. Population mean decision vector should remain the same before and after the recombination operator.
2. Variance of the intra-member distances must increase due to the application of the recombination operator.

Since the recombination operator does not use any fitness function information explicitly, the first argument makes sense. The second argument comes from the realization that selection operator has a tendency to reduce the population variance. Thus, population variance must be increased by the recombination operator to preserve adequate diversity in the population. The population mean can be preserved by several ways. One method would be to have individual recombination events preserving the mean between the participating parents and resulting offspring. We call this approach as the *meancentric* recombination. The other approach would be to have individual recombination event biasing offspring to be created near the parents, but assigning each parent an equal probability of creating off springs in its neighbourhood. This will also ensure that the population mean of the entire offspring population is identical to that of the parent population. We call this latter approach the *parent-centric* recombination.

Recombination operators such as unimodal normal distribution crossover (UNDX), simplex crossover (SPX), and blend crossover (BLX) are mean-centric approaches, whereas the simulated binary crossover (SBX) and fuzzy recombination (Voigt et al., 1995[60]) are parent-centric approaches. *Beyer and Deb (2001)[59]* have also shown that these operators may exhibit similar performances if the variance growth under recombination operator can be matched by fixing their associated parameters. In this paper, we use UNDX and SPX as representative mean-centric recombination operators and a multi-parent version of SBX as a parent-centric recombination operator.

To implement the genetic algorithm technique, following parameters are to be selected:

- Population Size (n) – usually 200-1000.
- Number of Run – usually- 10

- Probability of Crossover ($p_c$) – usually -0.7-1.0
- Probability of Mutation ($p_m$) – usually -0.01-0.05

Basic guideline for computing $p_m$ are :

$$p_m \geq 1/n$$
$$p_m \leq 1/l$$

Where

n = Population Size
l = Length of the string.

**4.4 Advantages of Genetic Algorithm:**

Genetic algorithm have a number of advantage over other mathematical programming technique *Goldberg1989 [35]*. In the context of the optimization of the pipeline network design, some advantages includes the following:

1. GAs deal directly with a population of solutions at any one time. These are spread through the solution space, so the chance of reaching the global optimum is increased significantly.
2. Each solution consists of set of discrete pipe size. One does not does not have to round diameters up or down to obtain the final solution.
3. GAs identify a set of solution of pipeline network configuration that are close to minimum cost solution. These configurations may correspond to quite different design that can be compared in terms of other importance but nonquantifiable objectives.
4. GAs use objective function or fitness information only, compared with more traditional methods that rely on existing and continuity of derivatives or other auxiliary information.

* Genetic algorithms do not necessarily guarantee that the global optimum solution will be reached, although experience indicates that they will give near-optimal solution after a reasonable number of evalutions.

## V. Simulation Results

If the objective function is formulated in terms of cost, the vector that yields the lesser cost replaces the population member in the initial population. If the objective function is in terms of profit function, then the vector with greater profit replaces the population member in the initial population. This procedure is continued till some stopping criterion is met. This may be of two kinds. One may be some convergence criterion that states that the error in the minimum or maximum between two previous generations should be less than some specified value (standard deviation may be used). The other may be an upper bound on the number of generations. The stopping criteria may be a combination of the two as well. Either way, once the stopping criterion is met, the computations are terminated.

*Fig. (1.1)* shows the design problem outlined. The maximum number of compressors in branches 1, 2, and 3 are set at 4, 3, and 3 respectively. The input pressure was fixed at 500 psia at a flow rate of 600 MMSCFD, and the two output pressures are 600 and 300 psia respectively for branches 2 and 3. The total length of the branches 1 and 2 put together is constrained to be 175 miles, whereas the total length of the branches 1 and 3 put together is constrained to be 200 miles.

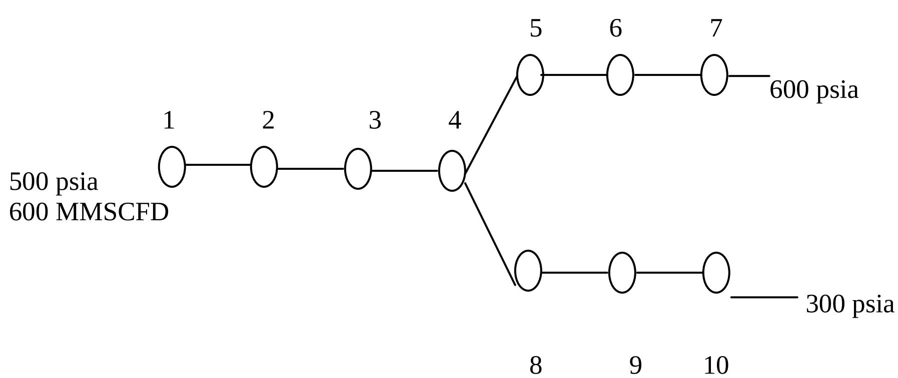


**Fig. 1.1 Initial Configuration of gas transmission network**

In the genetic algorithm formulation the eight decision variable in the case study network were each represented by a three bit binary substring representing eight possible alternatives as either new pipes, duplicated pipes or cleaning of an existing pipes. We have arranged the options for existing pipe in table 1 in term of the design parameter. The GA deals with a 24 bit binary string comprising the eight by three bit substrings representing the pipe network to be optimized. The Penalty cost for each loading case taken as the product of the maximum of all the pressure head constraint violations times a specified penalty Multiplier, K ( $/year). We choose value of K is very high.We develop a C program of a three operator GA couple with RGA tool. The program perform a hydraulic network analysis at each function evaluation in the hydraulic solver to minimise computation time.

The lower bound on the diameter of all pipeline segments is set at 4 inches. A lower bound of 2 miles is placed on each pipeline segment to ensure that the natural gas is at ambient conditions. The resulting solution obtained for suction **pressure range (300, 900) & K (1.2, 2.0)** to the design problem as shown in Fig.1.1 using the cost relation are shown in Fig. 1.2 & Table-1.

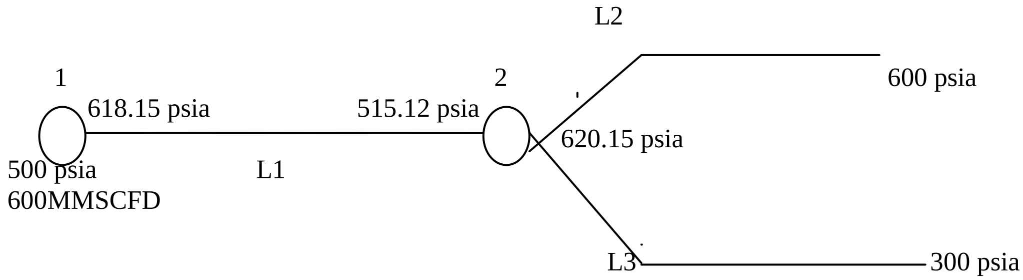


**Fig: 1.2. Final optimal gas transimission pipeline network for $p_s$(300, 900) & K(1.2, 2.0)**

**Table-1.** Results of Genetic Algorithm run for 1000 Evaluations for $p_s$(300, 900) & K(1.2, 2.0):

| $L_j$ | $p_d$ (psia) | $p_s$ (psia) | $D_i$ (inch) | Length (miles) | $Q_i$ (MMSCFD) |
|---|---|---|---|---|---|
| **1** | 618.15 | 515.12 | 41.87 | 110.00 | 600 |
| **2** | 620.15 | 600.00 | 39.18 | 65.00 | 300 |
| **3** | 620.15 | 300.00 | 26.14 | 90.00 | 300 |

As can be seen from the above results, all the constraints are satisfied with this optimal gas transmission network. Also, a single network has been obtained using GA .The optimum values of objective function is obtained as ***15712836 $/yr*** .

The resulting solution obtained for suction pressure range (300, 2000) & K (1.2, 5.0) to the design problem as shown in Fig.4.1 using the cost relation are shown in Fig. 1.3 & Table-2.

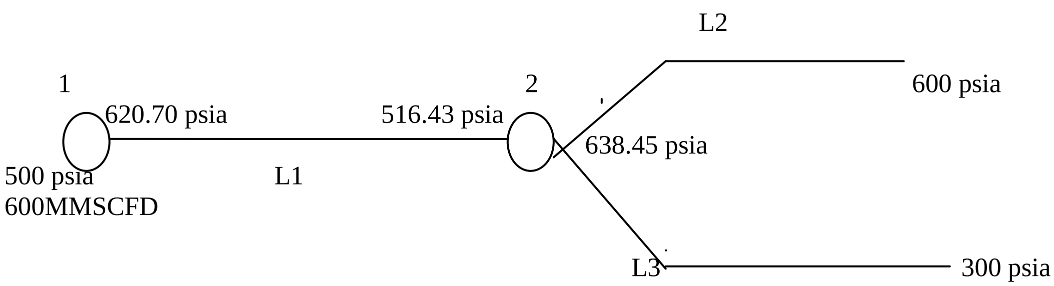


**Fig: 1.3**. **Final optimal gas transimission pipeline network for $p_s$(300,2000) & K(1.2,5.0)**

**Table-2:** Results of Genetic Algorithm run for 1000 Evaluations for $p_s$(300,2000) & K(1.2,5.0)

| $L_j$ | $p_d$ (psia) | $p_s$ (psia) | $D_i$ (inch) | Length (miles) | $Q_i$ (MMSCFD) |
|---|---|---|---|---|---|
| **1** | 620.70 | 516.43 | 41.75 | 110.00 | 600 |
| **2** | 638.45 | 600.00 | 34.61 | 65.00 | 300 |
| **3** | 638.45 | 300.00 | 25.78 | 90.00 | 300 |

As can be seen from the above results, all the constraints are satisfied with this optimal gas transmission network. Also, a single network has been obtained using GA. The optimum values of objective function is obtained as 14088050 ***$/yr***.

Now we can see from the above results, if we diversified the suction pressure range (300,900) to (300, 2000) and maximum compression ratio (1.2, 2.0) to (1.2, 5.0) then we observed no significant change in suction and delivery pressure of the compressor but due to significant reduction in the diameter of the second pipe seqment diversified the cost from 15712836 $/yr to 14088050 $/yr. Hence second solution is prominient one. So GA gives the more and more accurate result after number of alteration.

## VI. DISCUSSION

We have presented a methodology for the application of genetic algorithm technique to pipeline network optimization. The GA codes the pipe sizes available for selection as binary strings. We have used a simple three-operator genetic algorithm namely reproduction, crossover, and mutation. Results represented to show that the genetic algorithm techniques are very effective in finding near-optimal or optimal solutions for a case study network in relatively few evaluations.

The results from genetic algorithm technique have been compared with both complete enumeration and non linear optimization. One may only complete enumeration of pipeline network with relatively few pipes. Non linear optimization is an effective technique when applied to a small network expansions such as for the case study network; however, the problem of rounding up and down of continuous solution to discrete pipe size must be addressed.The non linear programming method only generate one solution. The GA technique generates a whole class of alternatives solutions close to optimum. One of these alternative solutions may actually be preferred to the optimum solution based on nonquantifiable measures. This is a major benefit of genetic algorithm method. The genetic algorithms technique is infancy, and further development should provide improvements in these search method for practical problem.

## VII. RECOMMENDATION FOR FUTURE WORK

The result of GAs depend on **Population Size, Number of run, Seed of random number, Probability of crossover, Probability of Mutation,** which is not covered in this project. In Future, we can study all above parameters and obtain the better results.

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## AUTHORS

**First Author** – Ram Ratan Singh (M.Tech-Pipeline Engineering), Officer-Projects, Pipeline & Projects Department, Hindustan Petroleum Corporation Ltd., Mumbai, India, Email Id: ramsingh@hpcl.co.in, ramratan.yadav@gmail.com, Mob: +91-9045033895

**Second Author –** P K S Nain, Mechanical Engineering Department Noida Institute of engineering & technology Greater Noida