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A Modified Differential Evolution Algorithm to Optimize the Design of Gas Transmission Network

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ABSTRACT
A modified Differential Evolution (DE) is used in optimization of a gas transmission network. The goal is to reduce the annual operating and maintenance costs by optimizing many network parameters such as the number of compressors, lengths and diameters of the pipeline segments, flow rate in each pipeline segment, discharge and suction pressures at each compressor. The design must satisfy several constraints,. The values of some parameters are dependent on other parameters, which increases the complexity of the network, using the standard DE technique. Hence, A modification strategy is needed to improve the searching for the global optimum values. The modified DE has been successfully applied to this complex and non-linear problem and needed a very shorter computational time to converge to the optimal solution. Previously, this problem was tackled using many techniques including nonlinear programming and DE techniques on a certain network configuration and setting. However, their optimal solutions did not satisfy all constraints, and the costs were still high compared to the results obtained by the modified DE algorithm. In addition, the proposed modified algorithm can be used for any network configuration. The modified Differential Evolution algorithm is presented here and compared with the previously used ones.

Keyword: Algorithms, Differential Evolution, Optimization, Constraint.

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I. INTRODUCTION

The design of the gas transmission network is one of the classical non linear constraint problems in chemical engineering [1, 2]. The design of the network is primarily concerned with reducing the annual cost of operation, maintenance of the gas transmission network. The design needs to have the minimal possible cost while operates as required and does not violate any of the design constraints. A gas transmission network is made of several connected pipeline segments, compressor stations at several sites to maintain the pressure, a source of gas and several destinations at the end points. The design of an efficient gas transmission network involves Differential Evolution (DE), developed by K. Price and R. Storm [3], is one of the best evolutionary computation methods. The convergence speed of DE is considered high and DE has been successfully applied to many complex problems.

Many people have worked on several aspects of gas transmission networks, and others have actually designed it. Larson and Wong [4] determined the optimal suction and discharge pressures of a straight pipeline with compressors connected in series, while the length and diameter of the pipeline segment were kept constants. Martch and McCall [5] added branches to the pipeline segments. Cheesman [6] applied a computer optimizing code to the Martch and McCall [5] problem where the length and diameter of the pipeline segments were variable.

The first major contribution to the optimization of the design of the gas transmission network came from Olorunniwo [7] and Olorunniwo and Jensen [8]**.** They used dynamic programming with optimization logic and included many design factors such as: maximum number of compressors, location of compressor stations, minimum recommended thickness of the main pipe, optimal diameter sizes, thicknesses and lengths of any required parallel pipe loops on each arc of the network, operating pressures of the compressors and the gas flow rate in the pipelines.

The second major contribution was by Edgar & Himmelblau [9] where linear programming was used to optimize the solution by making sure that the design factors are clear. An assumption was made for the gas quantity to be used in the problem statement. They figured out that by optimizing the number of compressor stations, the length of pipeline segments between the compressors stations, the diameters of the pipeline segments, and the suction and discharge pressures at each compressor station, then the objective function would result in an optimal value. In 2003**,** Babue and Rakesh [10] used DE to solve the same problem configuration and formulation used in [9] and proved that DE will result better convergence speed while maintaining all constrains, the thing that Edgar & Himmelblau could not fully satisfy using non-linear programming techniques.

In this paper, a modified differential evolution technique is introduced and applied for the optimization of a gas transmission network design. A network similar to the one presented in [9] and [10] was used as a model, and results of the two techniques were compared. The modified technique can be applied to any network configuration.

This paper is organized as follows. The second section will present the network model design. Section 3 will introduce the Differential Evolution algorithm while the Modified DE algorithm will be discussed in section 4.Experimental results will be shown in section 5. Finally, some conclusions will be briefed in section 6.

II. MODEL DESIGN

The Gas pipeline network to be studied consists of a number of compressor stations. Each of the compressor stations is represented by a node and each of the pipeline segments by an arc as shown in Fig 1 [9, 10]. The system is assumed to be horizontal with the pressure increases at a compressor and decreases along the pipeline segment away from the compressor in the direction of the flow of the gas. A much more complicated network with various branches can also be considered. The capital costs ofthe compressors are a linear functions of horsepower. From the configuration in Figure 1,it can be seen that for *N* compressors, there must be *N+1* pipeline segments, each segment with a certain length and diameter. Also, there are *N-1* suction pressures and *N* discharge pressures. In addition to the diameter and length, each segment has an associated flow rate, with a predefined initial and outlet pressures. Since the flow rate is fixed, it is only need to determine the initial pressure, outlet pressure, pipeline diameter and length for each segment.

The following assumptions are made:

1. Pipeline segment is long enough so that by the time gas reaches the next compressor it returns to the ambient temperature.
2. The annual 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 [5].
3. Total operating costs are linear function of compressor horsepower (Operation and maintenance costs per year can be related directly to horsepower [11] and have been estimated to be between 8.00 and 14.0 \$/(hp)(year) [3].

The fitness function F is used to calculate the total annual cost in US dollars including operational and maintenance costs for the compressors and the pipeline segments together. Fitness function is used to minimize the cost and is given by equation (1) [10]:

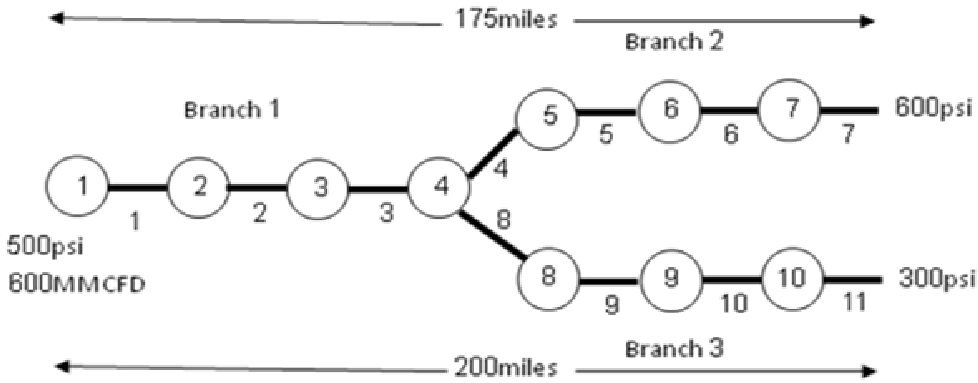

Figure 1: Simple gas transmission network with fixed total branch lengths

$$F = \sum_{i=1}^{n} (C_0 + C_c)\, Q_i (0.08531)\, T_i [\, k/(k-1) \left[(P_{di}/P_{si})^{z(k-1/k)} - 1 \right] + \sum_{j=1}^{m} [C_s L_j D_j] \qquad (1)$$

Where,

n = number of compressors in the system

m = number of pipeline segments in the system (m = n + 1)

C_0 = annual operating cost = 8.0 \$/(hp)(year)

C_c = compressor capital cost = 70 \$/(hp)(year)

k = C_p/C_v for gas at suction conditions = 1.26 [12]

z = compressibility factor of gas at suction conditions = 0.88
P_s and P_d = suction pressure and discharge pressure respectively, psia
T_i = suction temperature = 520R
Q_i = flow rate into the compressor (million cubic feet per day)
C_s = pipe capital cost = 870 $/(in)(mile)(year)
L_j = length of pipeline segment j, mile
D_j = diameter of pipeline segment j, inch
There are many constraints that should be satisfied when the network is designed such as:
The discharge pressure is always greater than or equal to the suction pressure in the operation of each compressor such that $P_{di} / P_{si} \geq 1$ for i = 1, 2, 3, …, n

Also at each compressor, the compressor ratio should not exceed some pre-specified maximum limit *K i.e.* $P_{di} / P_{si} \leq K$ for i = 1, 2, 3, …, n and *K=2.*
There are upper and lower bounds for each of the given four variables:

$P_{di}^{min} \leq P_{di} \leq P_{di}^{max}$, $P_{si}^{min} \leq P_{si} \leq P_{si}^{max}$, $L_i^{min} \leq L_i \leq L_i^{max}$ and $D_i^{min} \leq D_i \leq D_i^{max}$
A quality constrain is set on the total lengths of the segment for each branch. For example, the total length of all segments for branch 1 is the sum of all the main branch segments and branch 1 segments:

$$\sum Li \text{ (for the main branch)} + \sum Li \text{(for branch 1)} = L1$$
&
$$\sum Li \text{ (for the main branch)} + \sum Li \text{(for branch 2)} = L2 \quad (2)$$

Where L1 and L2 are fixed lengths specified at the design step**.**
Each pipeline segment must satisfy the Weymouth flow rate equation [13]:

$$Q_i = 871 D_i^{(8/3)} [(P_d^2 - P_s^2)/L_i]^{(1/2)} \quad (3)$$

Where Qi is a fixed number and P_d & P_s are the discharge pressure & suction pressure at the entrance and exit of the segment respectively.

To evaluate the efficiency of the adopted modified DE algorithm, it was applied to a network configuration that has been optimized using linear programming in [9] and DE in [10]. The network configuration is shown in Fig 1 consisting of 10 compressor and 11 pipeline segments, with an inlet pressure of 500 psi and a flow rate of 600 MMCFD, outlet pressures of 600 and 300 psi for the last segments of branch 1 and branch 2 respectively. The Length of L1 and L2 are set to 175 and 200 miles and all the previously stated parameters are applied.

III. DIFFERENTIAL EVOLUTION DE

Differential evolution is an evolutionary algorithm originally proposed by Price and Storn [3]**,** whose main design emphasis is real parameter optimization. Differential Evolution is based on a mutation operator, which adds an amount obtained by the difference of two randomly chosen individuals of the current population, in contrast to other evolutionary algorithms, in which the mutation operator is defined by a probability function.

The basic algorithm of differential evolution is shown in Fig 2, where the problem to be solved has n decision variables, fitness function F and Crossover Probability CR parameters are given by the user, and Xi,j is the i-th decision variable of the j-th individual in the population. Authors of the differential evolution algorithm have suggested that by computing the difference between two randomly selected individuals from the population, the algorithm is actually estimating the gradient in that zone (rather than at a point). This approach constitutes an efficient way to self-adapt the mutation operator. Furthermore, the local criterion of the selection operator is efficient and fast when using DE. The version of differential evolution shown in Fig 2, is called DE/rand/1/bin, and is recommended to be the first choice when trying to apply differential evolution to any given problem. However, there are some other versions of the differential evolution algorithm and the modifications made here to the variation operator may have certain similarities with some of those versions.

```
Generate initial population of size NP
Do
  For each individual j in the population NP
        Generate three random integers, r1, r2 and r3 between [1, NP], where r1 ≠ r2 ≠ r3 ≠ j
        For each gene i within the individual j
                If rand[0, 1] ≤ CR                                  {Crossover}
                  Uji = Xr3i + F (Xr1i − Xr2i)                      {Mutation}
                Otherwise
                  Uji = Xji
        End For
        Replace Xj with the child Uj if Uj has better fitness
```

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            Otherwise
            Keep Xj
    End For
Until the termination condition is achieved
```

Figure 2: Pseudo-code of the differential evolution algorithm adopted in this work (this version is called DE/rand/1/bin)

IV. MODIFIED DE TECHNIQUE

The proposed approach is based on the basic DE algorithm which was described in the previous section. Necessary modifications were applied to the Initial population generation and to the Mutation steps.

In the initial population generation step, the process of randomly regenerating the individual was eliminated if it was not satisfying all constraints. Instead, for individuals with related constraints, such as P_d & P_s, all the possible scenarios were evaluated and by calculating new boundary values, this will force the generation of the random numbers to be within the defined boundaries in order to get a random individual which satisfies the constrains. The pseudo-code for this step is shown Fig 3.

In the generation of the initial population, it was found that it is better to generate P_d for all segments such that it falls between the maximum and minimum boundaries. Then, while generating *Ps* for each segment *i*, the compressor ratio constraint must be satisfied and to do so, two different scenarios exist. First, if the discharge pressure at the current pipeline is less than or equal to the discharge pressure at the next segment ($P_{di} \le P_{d(i+1)}$). Second scenario is when $P_{di} > P_{d(i+1)}$. In both scenarios, we have to check that P_{di} is less/greater than $P_{d(i+1)}$ by how much and whether it is less/greater than by half/twice or the other way around. However, while generating P_{si}, we might need to change P_{di} or $Pd_{(i+1)}$ in order to satisfy all constraints.

```
Generate initial population of size NP such that each individual satisfies all boundaries constrains and relational constrains
  For each individual j in the population NP
        For each Gene i in the individual j
              Generate a random value Xji such that Xji (Min) ≤ Xji ≤ Xji (Max)
              [while generating each Psi check the following:
                    If Pdi ≤ Pd(i+1) then
                          If Pdi is less than Pd(i+1) /2 then
                                Pdi = Pd(i+1) /2 + rand[0,1] * Pd(i+1) /2
                    Psi = Pd(i+1) /2 + rand[0,1] * (Pdi - Pd(i+1) /2)
                    else
                    If Pdi > Pd(i+1) then
                          If Pdi is greater than 2*Pd(i+1) then
                                Pd(i+1) = Pdi /2 + rand[0,1] * Pdi /2
                    Psi = Pd(i+1) /2 + rand[0,1] * (Pd(i+1) /2)

              If Ps < Pmin then Ps = Pmin ]
        End for
  End for
```

Figure 3: Modified initial population generation

```
Modified Mutation
  For each individual j in the population NP
        Choose three random numbers r1, r2, r3 such that r1 ≠ r2 ≠ r3 ≠ j
          For each Gene i in the individual j
              If rand[0,1] ≤ CR
                    Uji = Xr1i + [(Xmax - Xr1i)/ Max(Xr1i , Xr1i)] */ Xr3i – Xr2i]

              [ while mutating each Psi check the following:
                    U(Ps)i = Psr1i + [(U(Pd)i - Psr1i)/ Max(Psr1i , Psr1i)] */ Psr3i – Psr2i]

                    If U(Pd)(i+1) > 2*[Psi + (Pd(i+1) - Psi)] then
```

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                                    U(Ps)i  = Psr1i + [2* (U(Pd)i - Psr1(i+1) )/ Max(Psr1i , Psr1i)] */ Psr3i – Psr2i]
                                If U(Pd)i < U(Ps)(i-1)
                                    U(Pd)i = U(Ps)(i-1) + (Pmax – U(Pd)i )/ Max(Psr1i , Psr1i)]  * [ Psr3i – Psr2i]
                                If U(Pd)i < U(Ps)i
                                    U(Pd)i = U(Ps)i + (Pmax – U(Pd)i )/ Max(Psr1i , Psr1i)]  * [ Psr3i – Psr2i]
                 ]
                 Else
                                Uji  = Xji
        End for
End for
```

Figure 4: Modified Mutation

Similarly, in the mutation step, It was discovered that the same approach should be followed while mutating P_d and P_s values in order to maintain the values within the constrains. This step is less complicated than the initial generation of the individuals because all individuals are required to satisfy constrains, and the challenge is to find a new child using three other individuals such that the constraints are satisfied and if not, maintain the value of P_{di} to satisfy the compressor ratio constraint.

V. RESULTS

CASE1: When the modified DE algorithm was applied to the network with number of population of 50 (NP=50), Crossover Probability of 0.3 (CR=0.3), and 5000 generations (NG=5000), the fitness function value was $3.0452 Million/yr. Graphical analysis of the solution is shown in Fig 5. All solutions converged to the same value after 2000 generations.

CASE2: Then, CR was changed to be 0.5, NG to be 2000, and NP= 50. The fitness value improved to be $2.53237 Million/Yr. It also converged in almost half the time that was needed for case 1 as shown in Fig 6.

CASE3: CR was set at 0.8 instead while keeping CR and NG similar to case 2, the convergence of the fitness function was $ 2.80732Million/Yr, which is higher than case 2 . However it was noticed that the convergence speed is much faster. This means the greater CR the faster the convergence. However, this does not mean better fitness. See Fig7.

Similarly, experiment was repeated for NP equals 100 and CR 0.3, 0.5, 0.8 and 1.0 respectively. All the results are shown in Table 1. The resulting optimum values of network design parameters that satisfy all constraints are shown in Table 2

VI. CONCLUSIONS

The experimental results presented in previous section can be used to draw the following conclusions: The best fitness (lowest cost) was $ 2.31724 Million/Yr which is obviously better than the fitness costs obtained using Linear Programming ($7.389 Million/Yr) [9] and using DE ($7.792 Million/yr) [10], with all constraints satisfied. The best fitness value was achieved with NP=100, CR=0.5, and NG=2000 where it was noticed that higher value of CR leads to a faster convergence but with higher cost. Therefore, CR value of around 0.5 was found to be a good compromise. Furthermore, The modified DE significantly reduced the computation time, since it forced the randomization process to give a valid random value. Finally, it was observed that the segments pipeline diameter is the major factor on total fitness cost as it has an impact on the flow rate.

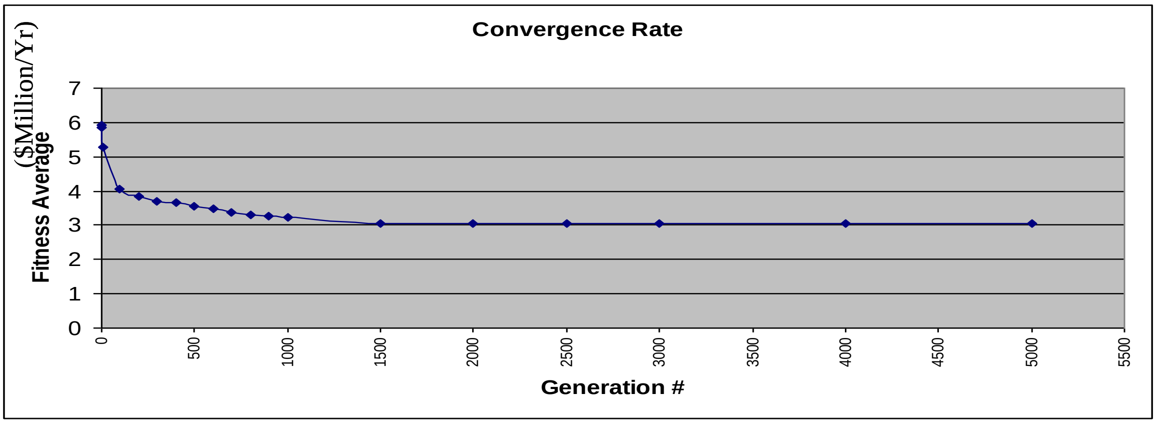

Figure 5: Apply MDE with NP=50, CR=0.3, and NG=5000

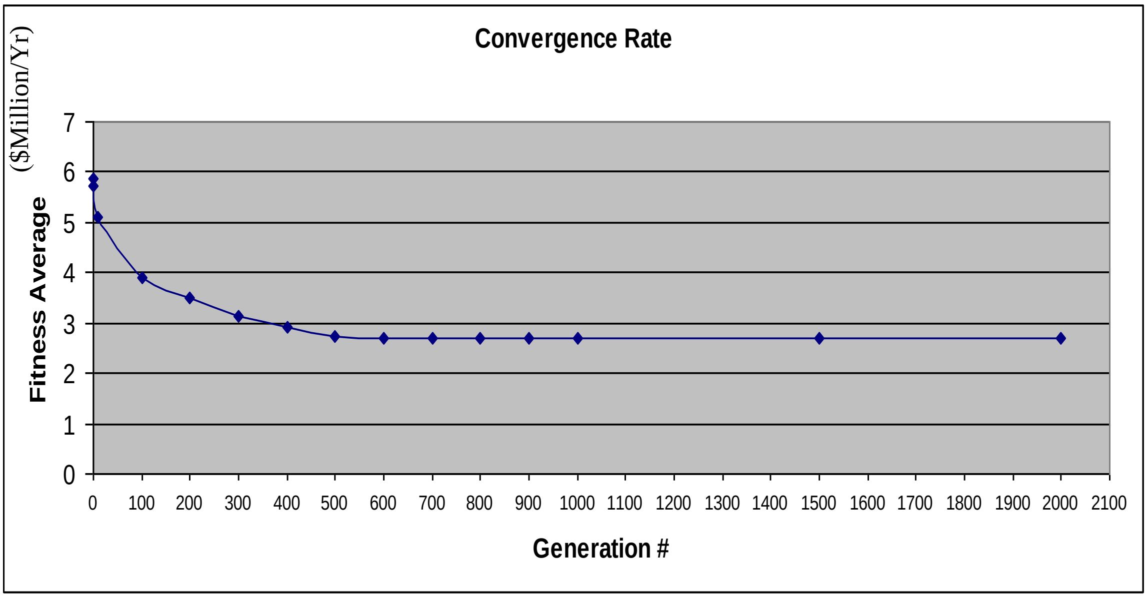

Figure 6: Apply MDE with NP=50, CR=0.5, and NG=2000

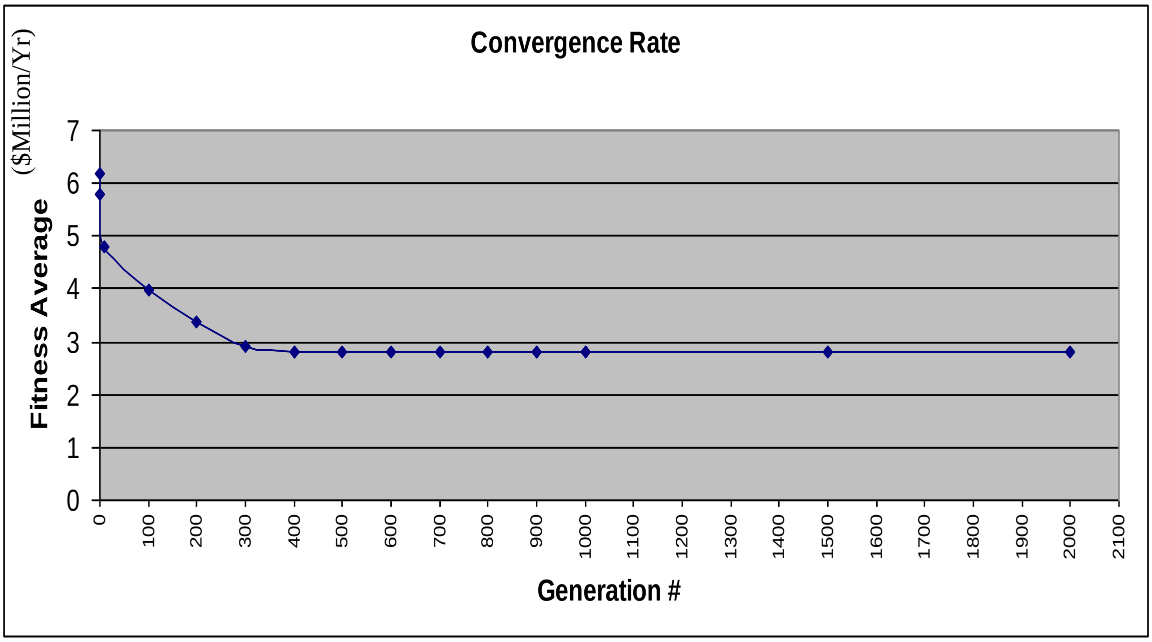

Figure 7: Apply MDE with NP=50, CR=0.8, and NG=2000

Table 1: Summary of experimental results

NP	CR	Fitness ($million/yr)	Convergence speed
50	0.3	3.0452	At Gen. # 1500
50	0.5	2.68613	At Gen. # 700
50	0.8	2.80732	At Gen. # 400
50	1.0	3.17538	At Gen. # 400
100	0.3	2.94531	At Gen. # 2000
100	**0.5**	**2.31724**	**At Gen. # 1000**
100	0.8	2.54418	At Gen. # 500
100	1.0	2.67166	At Gen. # 500

Table 2: The optimum design using Modified DE algorithm

	P_d (psi)	P_s (psi)	D_i ((inch)	L_i (mile)	Q_i (MMCFD)
Segment1	714.132	464.149	5.0098	26.3929	6.76146
Segment2	555.536	479.436	19.4682	16.1563	166.803
Segment3	955.687	927.864	7.67296	18.6925	10.5627
Segment4	941.673	747.42	16.0829	19.8475	184.563
Segment5	752.623	603.057	9.34544	16.7031	37.1862
Segment6	937.229	933.426	17.4672	9.23348	49.6544
Segment7	941.063	600	4.42854	67.9741	4.05074
Segment8	973.005	772.448	15.0896	3.3024	394.294
Segment9	772.448	592.707	8.42256	26.7996	24.4748
Segment10	612.278	489.033	12.0423	14.9737	63.1804
Segment11	781.566	300	4.62337	93.6825	3.85271

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