Fast and Accurate Reservoir Modeling: Genetic Algorithm versus DIRECT Method

Mohsen Ebrahimi, Milad M. Rabieh

Abstract—In this paper, two very different optimization algorithms, Genetic and DIRECT algorithms, are used to history match a bottomhole pressure response for a reservoir with wellbore storage and skin with the best possible analytical model. No initial guesses are available for reservoir parameters. The results show that the matching process is much faster and more accurate for DIRECT method in comparison with Genetic algorithm. It is furthermore concluded that the DIRECT algorithm does not need any initial guesses, whereas Genetic algorithm needs to be tuned according to initial guesses.

Keywords—DIRECT algorithm, Genetic algorithm, Analytical modeling, History match

I. INTRODUCTION

DIAGNOSTIC analysis, manual type curve matching, analytical modeling, and numerical modeling are the techniques that are usually used for well test interpretations. Diagnostic analysis and type curve matching are also called graphical analysis, which relies heavily on graphics. In graphical analysis, the data and their derivative are graphically displayed in both normal and dimensionless formats on linear and / or log scales. The most important plots of diagnostic analysis are semi-log and log-log plots of pressure response against time. Semi-log analysis is based on the location and interpretation of the semi-log straight line response (infinite acting radial flow) [1]. Log-log analysis is usually based on the interpretations of pressure data and its derivative in wellbore storage, and radial flow regions.

Diagnostic analysis uses only part of the data to estimate the unknown reservoir parameters. Since the early part of the reservoir response is usually overshadowed by wellbore storage effects, it is needed to wait until the infinite acting response is reached and that is about 1½ log cycles farther [1]. Type curve matching uses this transitional data in analysis as well. In manual type curve matching the user is able to move the well test data on a set of predefined type curves until a match is achieved between the data and the type curve. Then it is possible to calculate parameters such as permeability, skin factor, and storage coefficient through match point [2]. This relies heavily on user's ability to accurately fit the data to the type curve.

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Analytical modeling or automated type curve matching is entirely different from graphical techniques in that it uses nonlinear regression to match the observed data to a chosen reservoir model [1]. The matching is achieved by changing the values of the unknown reservoir parameters (such as permeability, skin factor, storage coefficient, distance to boundary, etc.) until the model and the data fit as closely as possible (in a least squares sense) by minimizing the sum of squares of the differences between measured pressure and model pressure. Thus there are significant cases of tests which are interpretable by nonlinear regression but not by graphical techniques, such as those that terminated prior to reaching the semi-log straight line [1].

Numerical analysis consists of representing the reservoir around the tested well by suitable grids that can be simulated through finite difference or finite element methods. Numerical modeling usually gives more accurate results for wells producing in a heterogeneous reservoir or having a non-circular drainage area.Many algorithms have been developed to be used in non-linear regression problems, including Newton-Raphson, Gauss, Gauss-Marqardt, Gauss-Newton, Lagrange, and most recently genetic algorithm. Except genetic algorithm, all of these techniques need initial guesses of reservoir parameters. Genetic algorithms is a method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution. The problem in using genetic algorithm is its sensitivity to tuning. In other words, the selection, mutation, and crossover rules must be tuned for different kinds of problems so that the algorithm can give an accurate result in a logically short period of time. The problem is that without the knowledge of initial guesses, a proper tuning cannot be performed.In this study, an alternative approach for solving least square minimization is presented, which will evaluate well test parameters without initial guesses. The results of the new method, DIviding RECTangles (DIRECT), will then be compared with the results of genetic algorithm as one of the best optimization solutions. Genetic and DIRECT algorithms are briefly described below.

II. BACKGROUND

The history and description of genetic algorithm can be easily found in different books and papers on the subject. A detailed description of the DIRECT algorithm can be found in [3]. Since a complete review of these topics is difficult to achieve in this study, only a brief description of the subjects is given:

A. Genetic Algorithm

The genetic algorithm (GA) is a stochastic optimization algorithm that mimics the process of natural evolution. In a genetic algorithm, a population of random possible solutions evolves toward better solutions. The population size depends on the nature of the problem, and although it is random, it must cover the entire range of possible solutions. Sometimes, the solutions may be weighted in areas where optimal solutions are likely to be found.

During each successive generation (iteration), a fitness function is used to evaluate the fitness of the existing population. Fitter solutions are then selected and modified to form a new population. This is performed using different selection functions such as stochastic uniform, uniform, shift linear, roulette, etc.

Modification of the new population or the reproduction of children from their parents happens through cross-over and / or mutation. The children share many of the characteristics of its parents. Crossover combines two individuals, or parents, to form a new individual, or child, for the next generation. Mutation functions make small random changes in the individuals in the population, which provide genetic diversity and enable the genetic algorithm to search a broader space. This should allow the algorithm to avoid local minima by preventing the population of chromosomes from becoming too similar to each other.

This generational process is repeated until a termination condition such as producing a maximum number of generations, or reaching a satisfactory fitness level for the population is achieved.

From this brief description it is evident that genetic algorithm has many parameters to be tuned. Population size, crossover function, cross fraction, mutation function, selection function, generations, and many more parameters must be tuned for a genetic algorithm to result accurate results.

B. DIRECT Algorithm

The DIRECT (DIviding RECTangles) introduced by Jones et al. [3], is an optimization algorithm designed to search for global minima of a real valued function over a bound-constrained domain. The two main components of the DIRECT are its strategy of partitioning the search domain, and the identification of potentially optimal hyper rectangles, i.e., having potential to contain good solutions. [4].

In DIRECT algorithm, the search domain is first scaled to an n-dimensional unit hyper rectangle. The function is then evaluated at the center of this hyper rectangle, which is considered potentially optimal. In the next step, the function is evaluated at one-third of the distance from the center in all coordinate directions. The DIRECT then moves to the next phase of the iteration, and divides the first potentially optimal hyper rectangle. The division procedure is done by trisecting in all directions. The trisection is based on the directions with the smallest function value. This is the first iteration of DIRECT. The second phase of the algorithm is the selection of potentially optimal hyper rectangles.

Assuming that the unit hypercube with center ci is divided into m hyper-rectangles, a hyper-rectangle j is said to be potentially optimal if there exists rate-of-change constant $\tilde{K}$, such that equations 1 and 2 are met:

$$f(c_j) - \tilde{K}d_j \leq f(c_i) - \tilde{K}d_i \qquad (1)$$

$$f(c_j) - \tilde{K}d_j \leq f_{\min} - \varepsilon |f_{\min}| \qquad (2)$$

Where fmin is the best function value found up to now, di is the distance from the center point to the vertices and is used here to protect the algorithm against excessive local bias in the search. ε is a parameter that is used to control the balance between local and global search and protects the algorithm against excessive emphasis on local search [4].

III. PROCEDURE

Figure 1 shows pressure drawdown during a constant-rate welltest. The wellbore had a falling liquid/gas interface throughout the drawdown test. Other pertinent data are presented in Table I. From the diagnostic analyses, a permeability of 10.62 md, a skin factor of 3.390, and a wellbore storage of 0.01 bbl/psi is obtained. Figure 2 shows the obtained parameters on the log-log plot.

This paper is an attempt to perform an analytical analysis without having initial guesses. Both genetic algorithm and DIRECT technique does not require initial guesses and hence are compared here. The matching process is run using MATLAB. The reason for choosing MATLAB is that it is a slower language in comparison with other programming languages and therefore, the run time allocated for each matching process can be compared more easily. It must also be noted that the genetic algorithm is not tuned here and uses the default settings in MATLAB

IV. RESULTS AND DISCUSSION

The plots and results of both genetic algorithm and DIRECT technique along with their allocated run times are presented below. Figure 3 shows the obtained match of an analytical model to pressure data using genetic algorithm after 37 seconds. Figure 4 shows another data match using genetic algorithm. This run takes 45 second and it seems that the run takes more time when the skin is negative, or at least the algorithm thinks is negative. As can be seen, the matches are quite different because the genetic algorithm uses random number generators and hence, the algorithm may return different results each time it is run. Figure 5 depicts the obtained match using DIRECT technique after only 6 seconds. The DIRECT technique is not based on random numbers; therefore, it returns the same results whenever it is run. The results of these three matches are shown in table 2. From the plots and results mentioned in this section, one can conclude that the genetic algorithm is very sensitive to the range it is going to look for the minimum function value. This range needs initial guesses to be specified. On the other hand,

DIRECT can accurately predict well test results in a relatively shorter time, which is a crucial enhancement for welltest analysis programs.

V. CONCLUSION

An attempt has been made to match a sample well test data for a reservoir with wellbore storage and skin to analytical models without setting any initial guesses for reservoir parameters. The obtained match is going to be found through minimization of least square errors between analytical model and pressure response data. Genetic algorithm and DIRECT technique are used to solve the non-linear regression. The genetic algorithm is already used for analytical modeling in some commercial well test analysis programs, but with initial guesses. DIRECT technique, on the other hand, has never been used for this purpose (to the authors' knowledge).

The results of different runs show that the genetic algorithm may give different results, each time it is run. This is because the genetic algorithm uses random number generators. DIRECT, on the other hand, is not sensitive to different runs and gives the same results each time. Furthermore, genetic algorithm takes more time for matching an analytical model, especially when a negative skin is taken into consideration. In contrast, DIRECT can give the match in a relatively shorter time while preserving its accuracy. The DIRECT method has not yet been used for analytical modeling and this paper's results show the advantages of using this technique in matching an analytical model to the welltest pressure response.

TABLE I
REQUIRED PROPERTIES FOR A SAMPLE WELL TEST INTERPRETATION

Parameters	Units	Values
Initial Pressure	psig	3000
Total Compressibility	1/psi	10E-6
Reservoir Thickness	ft	56
Flow rate	stb/day	500
Oil Viscosity	cp	0.8
Oil Density	lb/cu ft	50
Wellbore Radius	ft	0.3
Oil Formation Volume Factor	bbl/stb	1.2
Porosity	--	0.2

TABLE II
REGRESSION ANALYSIS RESULTS FOR DIRECT AND GENETIC ALGORITHM

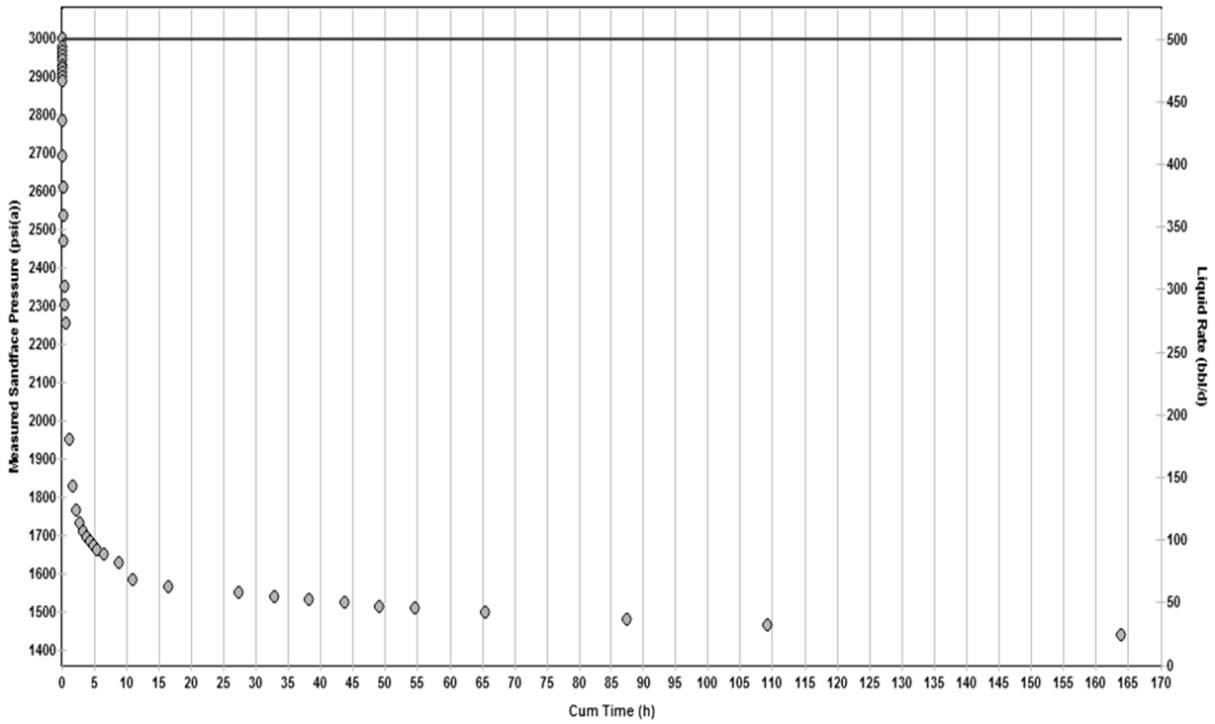| Solution Technique	MSE	Permeability (md)	Storage (bbl/psi)	Skin	Run Time
Genetic Algorithm Run 1	1.7892	9.833	0.009	3.32	36.82
Genetic Algorithm Run 2	4.1395	6.316	0.007	-0.24	45.08
DIRECT	1.5615	10.956	0.011	0.01	6.17

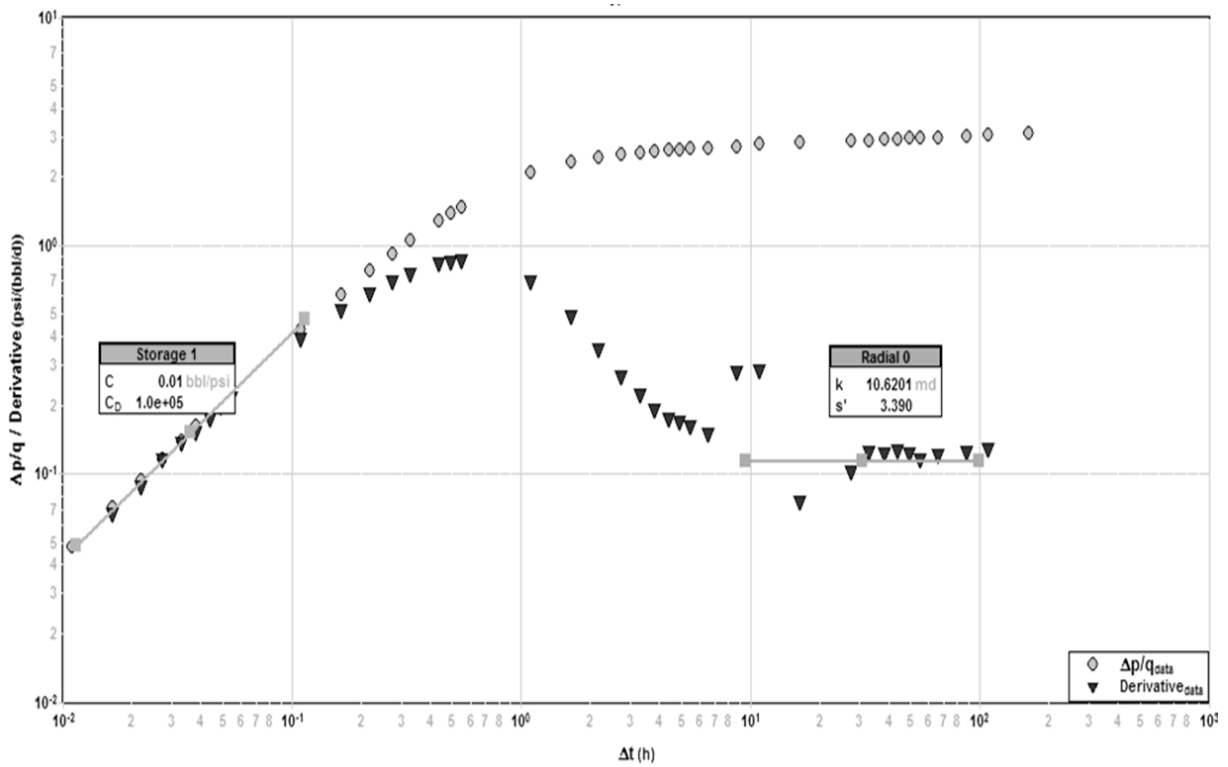Fig. 1 Pressure drawdown in a sample draw-down test

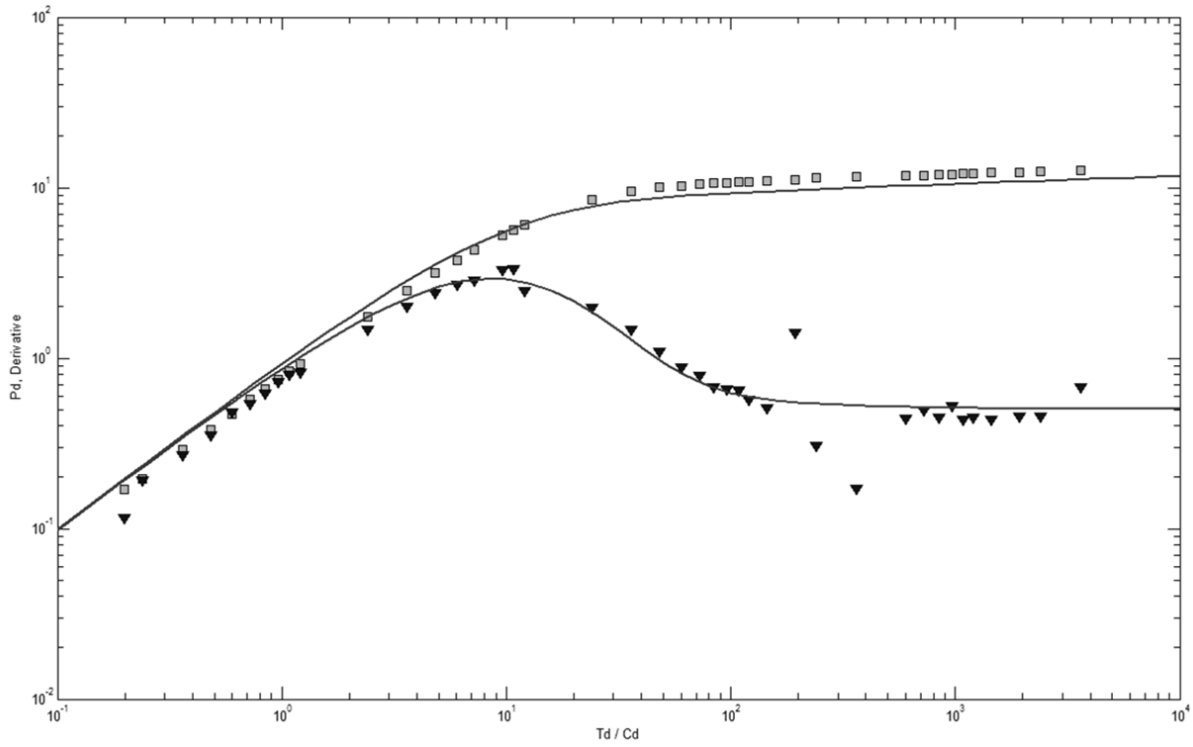Fig. 2 Log-log plot of pressure and its derivative versus time

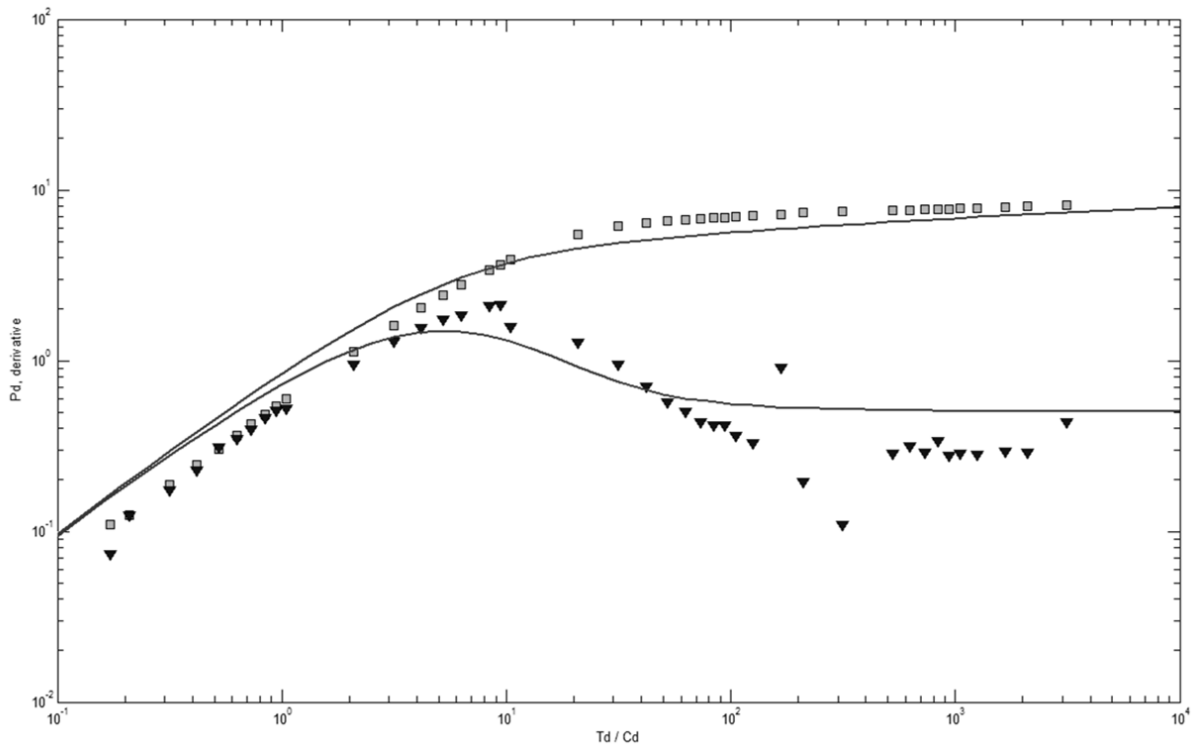Fig. 3 Obtained match using genetic algorithm, first run

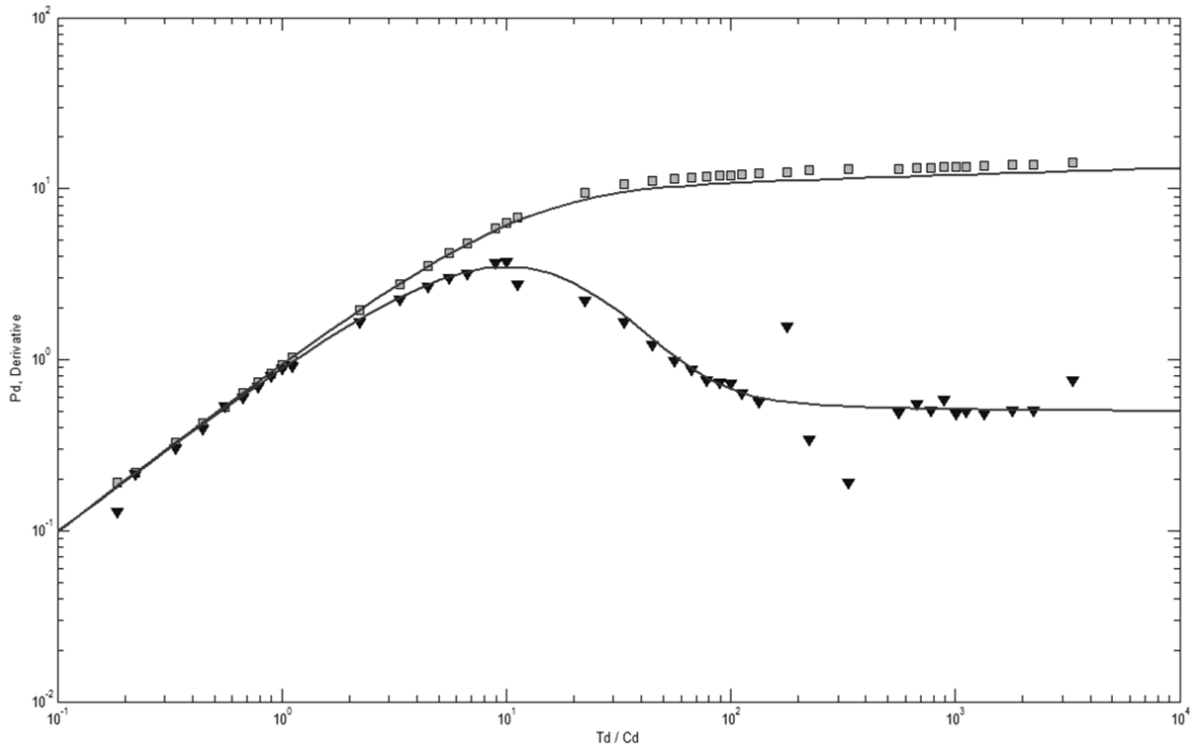Fig. 4 Obtained match using genetic algorithm, second run

Fig. 5 Obtained match using DIRECT technique, not run sensitive

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