Optimization Methods for History Matching of Complex Reservoirs

Abstract
Conventional direct optimization methods and Evolutionary Algorithms are applied to the problem of history matching in reservoir engineering. For the optimization of complex reservoir models the potential of parallel computing is investigated. Methods to improve the convergence of Evolutionary Algorithms by introducing expert knowledge are discussed.

An interface program has been developed which links an industry standard reservoir simulator to an optimization software package designed as a multipurpose environment for parallel optimization. Permeabilities, fault transmissibilities as well as relative permeabilities and barrier locations have been included in the optimization.

Results are presented for synthetic and real reservoirs with up to 30 wells and 40 design parameters. The potential and the „relevance of applicability of the optimization method to the problem of reservoir modeling in various modeling phases are discussed. The improvement of performance based on parallelism in a network environment is evaluated.

In conclusion, results suggest that Evolution Strategies can be successfully applied for generating possible solutions in the early modeling phase. The introduction of expert knowledge to the optimization methods is essential for reducing the multidimensional search space and improving convergence.

Introduction
Reservoir modeling becomes more difficult as the reservoirs become more complex and requirements for future production estimations need to be more accurate. In order to obtain an acceptable description of the reservoir many different simulation runs in completely different regions of the search space must be performed. Due to a lack of time and increasing pressure to produce results, test runs are often limited to a few “most plausible” sets of model parameters. This is the starting point of the concept followed in this paper. That is to define a methodology capable to support reservoir engineers to identify different starting points in a multi dimensional search space which have a high potential to generate calculated well production data which matches the measured data.

Usually limited information on the geological and geophysical background of the reservoir is available from well tests, seismic surveys, logs etc. Applications of reservoir simulations which intend to reproduce measured well production data on the basis of unknown model parameters define a procedure to solve the inverse problem of reservoir modeling. This procedure is often called history matching. History matching is defined by finding a set of model parameters which minimize the difference between calculated and observed measurement values like pressure and fluid production rates etc. In the special case of a gas storage for which season cycling gas injection and production are known, this might simply reduce to the pressure. More generally for a three-phase problem this will be pressure, oil, gas and water production rates as well as fluid contacts.

The procedure of history matching is time consuming and difficult. The formulation of the problem is of general nature and not reduced to history matching in reservoir engineering. In many engineering applications, simulations are based on a multidimensional solution space which generally contains a number of local optima.

For reservoir characterizations a number of previous works have concentrated on local gradient based optimization strategies 1,5. Gomez et al.2 have coupled a gradient method to a tunneling method with global optimization features. In order to accelerate the computation of large numbers of independent simulations, Letiö et al.3,4,7,8 have used direct optimization methods in connection with parallel computing. Most recently, Genetic Algorithms9,10 have been applied to reservoir characterization by Romero et al.

In this work we concentrate on Evolution Strategies which are generally robust and less sensitive to non-linearities and discontinuities of the solution space. One of the most challenging problems is the improvement of the convergence.

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In this context the introduction of heuristics derived from geostatistical information is discussed. The scope of this work is to analyze the potential of direct methods and in particular Evolution Strategies for optimizing large and complex reservoirs. We assume that the reservoir under investigation has a multidimensional search space, many wells (more than 20 wells) and it is characterized by a three-phase black-oil model. In addition, we assume that no information on the reservoir is available beyond geostatistical information, geological, seismic and history data.

For this purpose, an interface program was developed for linking a standard industry black oil simulator to the Multipurpose Environment for Parallel Optimization (MEPO). This optimization environment has previously been applied to various scientific and industrial engineering problems. In this work the application of Evolution Strategies to the problem of history matching in reservoir engineering is presented. The methodology is introduced and the implementation of Evolutionary Algorithms on parallel processors is addressed. Results are discussed on basis of a "virtual" reservoir model which is derived from a real North Sea reservoir.

Methodology
The choice of numerical methods supporting the process of history matching in reservoir engineering much depends on the formulation of the problem. The setup of an initial model requires different strategies and information compared to the fine tuning process once an acceptable history match is obtained. There is no tool which covers the whole range of tasks in history matching today. During the initial phase of setting up a reservoir model to be used for reservoir prediction, various combinations of model parameters have to be tested. At this stage several initial configurations are usable. The location of model parameters in a search space of possible realizations which are near optima is not known. Any numerical method which searches for local optima is therefore not appropriate to be used at this stage. Often initial reservoir models for simulation are derived from an upscaler geostatistical model. However, the upscaling process generates new uncertainties and the dynamics of the reservoir during production are usually not included. Therefore the search of model parameters near acceptable solutions needs to be repeated in the initial simulation phase. Once a location of acceptable parameters in the search space is found, local methods can be used to fine tune the model, i.e. to find the nearest optimum near any point in the search space which produces results close to an acceptable solution. In general gradient methods have proven to be quite successful in this domain. In addition, sensitivity analyses based on gradient methods can be used to determine model parameters which are most sensitive to the results in the vicinity of any point in the search space for which the gradients are calculated. This allows to reduce the number of model parameters to improve convergence and run times. Evolutionary Algorithms are capable to search beyond local optima and have the potential to identify configurations in the search space of model parameters which generate acceptable solutions.

Evolutionary Algorithms
Evolutionary Algorithms belong to the class of direct search methods. They use only the objective function value to determine new search steps and do not require any gradient information from the optimization problem. Therefore they can be used in cases for which gradient information are not available and where traditional algorithms fail because of significant non-linearities or discontinuities in the search space. Evolutionary Algorithms have proven to be robust and easy to adopt to different engineering problems. The nature of Evolutionary Algorithms is to use parallel structures in generating parent-to-child sequences. This principal feature can be easily transferred to parallel structures of an optimization program allowing parallel computing to be used. The scalability of this methodology will have an important effect on the applicability of numerical optimizations in case of very time consuming simulations.

Evolutionary Algorithms combining Genetic Algorithms and Evolution Strategies are used as well as Genetic and Evolutionary Programming - are defined by an iterative sequence of variation and selection operations. In most cases the type of parameters being changed by Genetic Algorithms is binary. Variations are performed by so-called Cross-over operations. In this work we focus on Evolution Strategies. They usually vary real or integer parameters by mutation operations which can be directly mapped to model parameters of the underlying optimization problem. A wide variety of different mutation operators are available and have been tested. Any solution obtained by the simulation is evaluated by the objective function. The selection is based on ranking objective values and allows to proliferate only the best individuals.

Application of Evolution Strategies to History Matching
Evolution Strategies use continuous and discrete parameters. In cases described in this paper the continuous parameters are permeabilities, transmissibilities and relative permeabilities. In addition, discrete parameters represent different realizations of permeability maps or the placement of barriers. In principal this list can be extended, e.g. parameters involved in the modeling of complex relative permeabilities for various processes (e.g. water alternating gas) and effects (e.g. hysteresis).

Each member of a population is qualified by an objective function value. A transition function describes a process of transforming a population into a subsequent one by applying mutation operators and selection criteria. A key advantage of Evolution Strategies is the simple translation of model parameters into the language of coded optimization parameters used by the optimization module. The implementation of modifications and the extension of the set of model parameters are generally straight forward.

Objective function
The difference between the observed values \( y_{\text{obs}} \) and calculated values \( y_{\text{calc}} \) defines the quality of the history match and is
described by the objective function $Q$. In addition, prior
information might be available from logs, cores, seismic or
geological interpretations. These information are included in
the prior objective function which is independent from the
observed and calculated measurement values.
There are different functional dependencies used in the
literature\textsuperscript{2,22}. The objective function used for calculations
presented in this paper is defined by\textsuperscript{22}

\[
Q = \frac{1}{2} \sum \alpha_j (y_j^{\text{calc}} - y_j^i)^2 \sigma_i^2 + \frac{1}{2} \sum x_n \left( \frac{\partial}{\partial x_n} \right) \left( x_n - x_n^i \right)
\]

where $y_j^{\text{calc}}$ are the calculated values and depend on the model
parameters $x_n$. Observed values $y_j^i$ are taken from the
production history. $\sigma_i^2$ define the variance of the observed
values. Measurement errors are assumed to be independent. In
order to prioritize the importance of the observed values a
weighting and normalization factor $\alpha_j$ is included. The
summation index $i$ refers in general to all wells, measurement
values and time steps. The prior objective function includes
additional information on the expected average value $\bar{x}_n$ and
the correlation matrix $C_x^{\text{prior}}$. Both types of information are
derived from geostatistical information. The summation
indices $n,m$ include all model parameters.

**Mutation**

In analogy to evolution in biology, minor changes in model
parameters occur more frequently than major ones. In the
simplest case, the mutation of a continuous parameter can be
achieved by multiplying initial parameters with normally
distributed random numbers. Usually different distribution
types have to be considered, depending on the geostatistical
information on model parameters. Initial parameters are
predefined and may vary between user defined limits.
Variations of the parameters are performed on basis of
individual step sizes.

**Step Size**

Special attention to the size of search steps is required for
Evolutionary Algorithms as well as for traditional
optimization methods. On the one side, any predefined range of
the search space limits the variation of the parameters. On
the other side, an adjustment to the local topology of the
search space is necessary to reach an optimum and helps to
improve convergence. If the step sizes are too large, an
optimum is only found by coincidence. If the step sizes are to
small, the optimization poorly converges and only the next
local optima will be found. At the beginning of the
optimization, the rate of variations should be set relatively
high. In the course of approaching an optimum the rate should
be reduced. Evolution Strategies modify the design parameters
with their individual step sizes. These step sizes are varied in
each iteration based on normally distributed random numbers.
In combination with the selection process an adaptive step size
adjustment can be established which maintains an efficient
approach towards an optimum.

In this work geostatistical realizations as well as the location of
barriers are represented by discrete values. Step sizes for
these design parameters can be treated as real numbers but
variations can only be performed based on discrete steps.
The causality of mutation has a difficult interpretation in the
case of the realizations. There is no logical ordering between
different realizations. Therefore small improvements of the
objective value cannot be linked to small changes of discrete
parameters which represent realizations in this case. An
adaptive step size adjustment cannot be established.

**Selection**

Mutations allow to change individual model parameter sets
and therefore increase the variability of a population. The
selection process intends to reduce the number of individuals
on the basis of an objective function which qualifies the result
of any simulation run.

Following the notation used for Evolution Strategies\textsuperscript{16,17}, a
competition between an initial parameter set (parent) and a
modified vector (child) by selection of the successor is called a
$(+)\text{ strategy}$. If the $(+)$ selection is generalized, this leads to a
$(\mu+\lambda)$ strategy, in which the $\mu$ parents compete with $\lambda$
children. The $(+)$ selection guarantees the preservation of the
best sets of model parameters over as many generations until
they are replaced by further control mechanisms. So called $(\_)$
strategies sometimes remove even the best parameter sets of
earlier generations, since the selection procedure is focused on
children only. These selection strategies allow to leave local
optima.

In addition to these basic strategies, mixed forms allow to
change from one to another selection strategy during the
optimization by means of further control parameters.
Another method is to destabilize stagnating improvements
during the course of optimizations. A reduction of the quality
is accepted, allowing randomly selected parameter sets with
bad qualities to proliferate.

This mechanism will generally decrease the convergence,
however, it offers the possibility to leave a region near a local
optimum. Depending on the choice of step sizes, strategies and
destabilization the solution space can be tested to find global
solutions.

Fig.\textsuperscript{1} shows processes of a $(\mu+\lambda)$ strategy used in an Evolution
Strategy. The calculation of the measurement values
$y_j^{\text{calc}}(x)$ based on a set of model parameters $x_n$ is the most
time consuming part of the optimization cycle. The number of
communication processes are comparatively low. The nature of
Evolution Strategies favors the application of parallel
computations. In case of the example shown in Fig.\textsuperscript{1} all $\lambda$
simulations can be run in parallel. They are independent. This
is one key advantage of Evolutionary Algorithms in general.
The layout of the network of available processors can be
scaled with respect to the requirements defined by the
underlying optimization problem.
Heuristics
One limitation of applying Evolutionary Algorithms to complex and time consuming simulations is the convergence behavior. The evaluation of model parameters sets which improve a history match based only on classical mutation and selection routines without defined reduction of the search space requires a high number of generations in the optimization process. In other areas of application the implementation of heuristics has shown a significant reduction of the number of generations before an acceptable result was achieved. In the work presented in this paper, geostatistical information are used to reduce the search space.

![Diagram](image)

*Fig. 1 - Parallel application of a \((μ+λ)\) strategy used in an Evolution Strategy*

Geostatistical information are generally treated as prior information and are included in the objective function. In that case, the prior term of Eq. 1 qualifies the initial choice of model parameters and adds a corresponding contribution to the objective function, i.e. any choice of parameters which do not reflect the geostatistical information is penalized. This, however, leads to simulation runs on the basis of model parameters which are not acceptable with respect to the prior information. Since this procedure does not reduce the computation time it is essential to allow the selection of only those combinations of model parameters which are in accordance with the geostatistical information. In order to accelerate the convergence any heuristics must influence the choice of model parameters before the time consuming simulation is started.

In the present version we have included geostatistical information as follows. Regions are identified in which parameters are assumed to be correlated. Instead of including \(n\) model parameters of one kind, \(g\) geostatistical realizations based on the same \(n\) model parameters are generated. Each realization satisfies the prior geostatistical information and is therefore an acceptable configuration. The optimization algorithm then chooses among a discrete number of \(g\) realizations instead of arbitrary combinations among \(n\) continuous model parameters. With respect to the involved \(n\) model parameters the search space is reduced from the \(n\)-dimensional continuous space to a set of \(g\) discrete values which represent \(g\) different realizations. This procedure is repeated for each region.

**Parallel Computation**
Complex reservoir simulations with a large multidimensional solution space favor optimization methods which have a potential for parallel processing. Applications of comparable complexity indicate that the focus on this potential is essential for productive applications of optimization methods. Fig. 2 shows selected optimization methods with respect to the number of independent calculations which can be processed in parallel. The first diagram represents parallel processes for Evolutionary Algorithms. Starting from any parent configuration a number of children are generated. The selection algorithm generates a new set of parents. The simulation of the children configuration can be computed in parallel. In the case of the Gradient methods a numerical search for the best local direction is followed by several search steps towards the best objective value in this direction. In this sequence the determination of the derivatives can be computed in parallel. A similar technique can be implemented in a parallel Simplex algorithm. Once the search direction is defined any calculation of improved results is computed sequentially. In contrary to such fully or partly parallel iterative optimization algorithms a standard Coordinate method has no potential for parallel computation.

**MEPO - Multipurpose Environment for Parallel Optimizations**
A Multipurpose Environment for Parallel Optimizations (MEPO) used in this work has previously been applied to various scientific and industrial engineering problems. The architecture of the program system is designed to operate on an arbitrary number of available processors connected in a computer network, including multi-processor machines. The exchange of information between different modules is based on the Parallel Virtual Machine (FVM). This messaging system is independent on the operating system and generally satisfies operating requirements defined by...
heterogeneous network configurations. Some key features of MEPO include:

- Master-Slave concept based on the message-passing software PVM
- Modular design structure to include customized optimization routines and simulation codes
- Database structure which stores information on all started processes
- Master module which administrates information passed between independent processes
- Load and task management to control processes in case of breakdowns or lost connections etc. and to maintain computer resources during day and night times

The principal design architecture including communication links is summarized in Fig. 3. The initial configuration as well as model parameters, geostatistical information etc. are defined in the User Interface. The master module is the Parallel Optimization Interface which administrates and stores all information. It provides data to the Optimization Module and controls all communication processes as well as the overall performance. The Optimization Module receives results on the objective function connected to each individual set of model parameters and generates new sets of model parameters for the next generation.

For this work a Pre- and Post-Processing Interface between the Parallel Optimization Interface and an industry standard black oil simulator has been developed. Pre- and post processing modules are based on standard control and input structures to prepare and interpret input and output data of the simulator. A script language is designed to include any other optimization parameters. This feature allows to modify the optimization strategy with respect to new optimization parameters without changing the program system. In addition, the calculation of the objective value is an integral part of the interface.

In this paper we focus on Evolution Strategies. However, the optimization module can be replaced by any other optimization method, e.g. Genetic Algorithm\textsuperscript{16}, Simulated Annealing\textsuperscript{30}, Simplex Algorithm\textsuperscript{35}, Gradient methods or Coordinate methods. The question of applicability with respect to any of these methods much depends on the problem description.

![Diagram](Fig. 2 Optimization Methods and Potential for Parallelism)

**Fig. 2 MEPO Program Structure**

**Synthetic test case**

A complex, synthetic reservoir has been set up to test the method described in this paper. The basic features of the reservoir have been taken from a realistic North Sea reservoir. Changes have been made to create conditions for a difficult and realistic history matching process. 20 production wells have been introduced and 10 injection wells to maintain pressure. No aquifer influx was present.

The construction of the reservoir was characterized by a 52x40x8 simulation grid. The 8 simulation zones were grouped into three geological layers, which were arbitrarily named TopZ (zone 1-2), MidZ (zone 3-5) and BotZ (zone 6-8). 12 major uncorrelated regions were defined, i.e. four in each layer. Each region was divided into 3 to 6 subregions, depending on the number of producers in the region. The subregions within one region were assumed to be correlated and each of them is embedding one producer. In average there
were 5 subregions, i.e. the reservoir was characterized by an overall number of 60 subregions. A thin shale layer covering the entire reservoir was assumed to exist between the layer MidZ and BotZ. A top surface map of the reservoir is shown in Fig. 4.

A homogeneous porosity of 30% across the entire reservoir was assumed. Permeabilities were heterogeneously distributed across all regions and subregions. Horizontal and vertical permeabilities were uncorrelated between different regions and correlated between subregions. The communication between MidZ and BotZ in the area containing the shale layer was modeled by the introduction of transmissibility multipliers in z-direction.

Fig 4 – Synthetic reservoir with oil, gas, water distribution

The reservoir is described by a three-phase black-oil model with live oil and free gas. All simulation cases had water injection and the reservoir pressure was never below the bubble point pressure. A single set of relative permeability curves was used.

History data
History data was generated on basis of a realistic exploitation plan shown in Fig. 5. All 20 production and 10 injection wells are introduced within a two year simulation period.

Fig 5 – Exploitation plan

An overall production period of ten years was simulated with a plateau period of three years. History data for each production well were the bottom hole pressure as well as the water, gas and oil production rates.

Free gas has been produced for a relatively long period in addition to water and dissolved gas production. Therefore, production rates of all three phases had to be considered in the history matching process.

The reference values for the horizontal permeabilities in each region used for the history case are given in Table 1. Permeability values for four regions in each of the three layers are shown. The reference values for the vertical permeabilities were taken as 10% of the horizontal permeabilities in the same region and layer.

<table>
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<th>Layer</th>
<th>Region</th>
<th>1/5/9 [mD]</th>
<th>2/6/10 [mD]</th>
<th>3/7/11 [mD]</th>
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The oil-in-place is mostly concentrated in regions 3, 7, and 11. Although the permeability is not the highest in these regions, they contain the most important oil wells. Regions 1, 5 and 9 are characterized by the highest permeability values and wells in these regions produce large water volumes. They are closest to the water zones and to the injection wells.

The control parameter for the history matching is defined by the total reservoir volume. The simulated field oil rate is therefore expected to fluctuate around the synthetic history values also during the plateau period, cf. Fig. 5. The production scheme is considered to have a recovery factor of 51% after 10 years production.

Optimization parameters
In this work permeability and transmissibility parameters have been chosen as design parameters in the optimization process. Due to the large number of subregions different representations have been chosen. Vertical and horizontal permeabilities were defined for each region. In addition, 4 transmissibility multipliers were describing the barrier between layer MidZ and BotZ. For each subregion permeability multipliers were defined, i.e. altogether 60 multipliers for the vertical permeability and another 60 multipliers for the horizontal permeability were defined. The permeability range was between 150–2000 mD for the horizontal direction and 15-200 mD for the vertical direction. The range of the transmissibility multipliers in four different regions were limited to the range of 0.0 to 0.5 and 0.5 to 1.0, respectively.

Prior Information
In order to handle the large number of model parameters, different realizations for all correlated permeability values within each region were calculated. Each realization was characterized by a set of permeability multipliers and each set was an acceptable solution based on geostatistical grounds. The surface map in Fig. 6 shows a region which is divided into several subregions indicated by different colors (grey shaded areas). The center points of two different subregions define the
distance between them. On the basis of a spherical variogram function new parameters in neighboring correlated subregions are calculated via kriging\(^\text{10}\). Realizations are calculated with respect to subregions, not for each block of the reservoir. A normal distribution of all parameters within one region and a variance of 10% was assumed. For each region 5 different realizations were calculated.

This procedure allows to maintain a heterogeneous permeability distribution across the reservoir. At the same time the number of optimization parameters, changed by the optimization module is significantly reduced. The case under discussion was defined by 28 continuous and transmissibility parameters permeability (cf. Table 2) and 12 discrete parameters. Each discrete parameter was linked to one region and was indexing 5 different realizations.

Fig 6 – Map of the reservoir divided into regions and subregions. Regions are surrounded by a black solid line.

For all permeability parameters an upper and lower limit was defined by a range of ± 50% of the reference values for each parameter. Since the a priori information on the parameter values were included by the definition of the different realizations, the prior term in the objective function has not been recalculated as an additive contribution to the objective value of Eq.1.

Discussion of Results

This section discusses results of the application of Evolution Strategies to the synthetic test case. Fig.7 shows the objective function for 80 function calls. A \((2+4)\) strategy has been chosen, i.e. each generation is defined by two parents and four children. Out of each generation the two best sets of model parameters survive to define the starting point of the next generation. Any configuration of model parameters survives as long as no better results are found. In the plot the result with the lowest objective value of each generation is high lighted, i.e. altogether 19 best results out of 19 generations are retrieved and are connected by the thick solid line. The thin line indicates results for each function call. After 10 generations the objective value has dropped by 70% with respect to the initial value. The calculation of additional 9 generations improve the result by further 15%. Nevertheless, large oscillations of the objective values linked to each child among the last 9 generations indicate that the step size for changing model parameters is still too large to search for an optimum. The Evolution Strategy requires more runs to adopt the step sizes. This of course raises the question, at what time a local optimization method should be used to search for an optimum, starting from the set of model parameters linked to the best result obtained so far\(^\text{10,11}\).

Fig 7 – Objective value for 80 function calls. The lowest objective values in each generation are marked and connected.

In the optimization process there are too many parameters involved to be shown here with respect to their development in consecutive function calls. A representative example for a selected region which contains important production wells is given in Fig 8.

Fig 8 – Model parameter development. Horizontal and vertical permeabilities for all function calls are shown. Parameters linked to the lowest objective value in each generation are marked and connected.

Vertical and horizontal permeabilities used as input parameters are shown for all simulations. The solid line connects values linked to the best results of each generation. The dashed line shows input values for each function call. The development shows general trends. For the multidimensional
search space it is difficult to draw any links between certain permeability values and the objective value. In general the occurrence of various "acceptable" objective values linked to different configurations of the model parameters indicates the solution defined by acceptable history match is not unique. In order to show the variation of the model parameters Table 2 lists all continuous design parameters included in the optimization. They are given for the reference case, the initial and two "best" cases which correspond to the 18th (best) and the 12th (second best) generation. Even the two best cases show that the values can be quite different. From the reservoir engineering point of view none of these values could be initially ruled out. Commonly, the permeability values are expected to be linked to the measured values from well core measurements. In most cases, however, permeability values implicitly include all unknown model parameters which are not considered explicitly in the model. Therefore, they are not directly comparable with measured values. For evaluating best cases, they might be compared in a prediction study which goes beyond the scope of this paper.

Fig. 9 shows the match for pressure and production rates. In order to compare the results, the history data, the initial and best case is shown. The dotted line shows the best result obtained so far. The dashed line shows the initial case and the solid line references the history data.

In a separate optimization run the importance of different realizations with respect to the objective value was analyzed. All continuous model parameters defined for uncorrelated regions were taken from the best run and were fixed for an additional optimization test run. The discrete parameters representing the different realizations were only changed. The objective function was changing by ±10%, i.e. the realizations are indeed a correction to variations of the objective value. Similar results were found if the parameter sets other than the best were chosen. In summary, the major improvement originates from the model parameters of the uncorrelated regions. This is plausible, since realizations are imposing smooth variations of the permeability changes of 10% in each region. On the other hand, the range of average permeability values for each region are limited by ±50% with respect to the reference values.

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Barrier Location and Corey Exponents
A further test run was intended to prove the applicability of the optimization method to the location of barrier placements and variations of Corey exponents which define the functional dependence of relative permeabilities with respect to saturation. The barrier location was defined by x- and y-coordinates. The extension of the barrier was automatically adjusted to the boundary of the reservoir. Fig. 10 shows a
permeability map and the rectangular shape of the barrier. The corner location of the barrier $P_{c}(x,y)$ is modified by the optimizer and it increases or decreases the region separated by the barrier from the rest of the reservoir. Each barrier is defined by a transmissibility multiplier of 0.25. In addition, the Corey exponents for relative permeabilities of oil and water ($K_{ro}, K_{rw}$) were taken as design parameters.

Fig 10 – Permeability map of the reservoir. The barrier is indicated by a thick line in the North-Eastern part of the reservoir.

For this test case the reservoir characteristics were kept identical to the first case described in this work, however, dead oil was assumed in order to reduce the computation time for each simulation and no subregions were considered. On that ground history data were regenerated. Fig.11 shows the objective function for 240 function calls. Fig.12 shows the change of the optimization parameters, i.e. barrier location and Corey exponents.

Fig 11 – Objective function for 240 function calls. The lowest objective values in each generation are marked and connected.

Large oscillations of the objective values are observed. This is due to the fact, that moving the corner point of the barrier in x-

direction by a few blocks in the vicinity of a well location (cf. Fig. 10) might also move the location of wells from one side of the barrier to the other. This, however, has large effects on the calculated measurement values. Small changes of discrete values (cf. Fig.12) in this particular case has therefore large effects on the objective value. This case is an example for large discontinuities in the search space. Nevertheless, the optimization routine proves the capability to optimize the configuration. The search space defined by the four model parameters is comparatively small and the lowest objective values are linked to model parameters close to the reference values, as seen by comparing Figs. 11 and 12.

Fig 12 – Model parameter development. Corey exponent (upper diagram) and x-location of the corner point of the barrier (lower diagram) are shown for all function calls. Parameters linked to the lowest objective value in each generation are marked and connected.

In general this case proves the applicability of the method to arbitrary model parameters. It also exemplifies the simplicity to add new model parameters as design values. This is an important feature for any practical applications in reservoir engineering. In the course of reservoir studies, the set of model parameters may be changed or extended. These changes should be easily introduced to the optimization program which is clearly favored by Evolutionary Algorithms as described in this work.
Conclusion
Evolution Strategies have been successfully applied to complex problems of history matching in reservoir engineering. Algorithms and methodology have proven to be flexible to adapt to changing requirements which result from new model configurations or the inclusion of new model parameters.

Typical reservoir model parameters like permeability and transmissibility have been used in the optimization process. In addition, parameters like Corey exponents and barrier locations have been included in the optimization process. The convergence of Evolutionary Algorithms remains a challenging topic. The method as well as the implemented program structure of this work is well prepared to use the potential of parallel processors in order to accelerate the elapsed computing time. However, the largest potential for optimizing the method is based on heuristics. The convergence much depends on the expert knowledge implemented in the procedure in order to reduce the multidimensional search space. The formulation and the implementation of further "nuristics therefore remain the challenging goal for the future.

Results presented in this paper suggest to use Evolution Strategies to evaluate the search space for history matching in simulation studies. Based on best results obtained, local methods might be used in order to fine tune the results.

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Conclusions and opinions stated in this paper are those of the authors and do not necessarily represent those of the partner companies.

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