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-TOPIC-

Prediction of gas flow rates from gas condensate reservoirs through wellhead chokes using Shuffled Complex Evolution Algorithm

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Appreciation

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Dedication To:

To my source of tenderness, patience and motivation, without whom I would be nothing, who always give me hope to live and who sacrificed so much for me so that I could succeed in my life and for their prayers and encouragement in difficult times. to my dear mother and my dear father

May God bless Them.

To my brothers "Ayoub" and my dearests sisters Words are not enough to thank them for their support, God bless Them

To my grandmother

to my uncles and my friends

I dedicate this work to you with all of My love heythem

Dedication To:

My parents: source of our courage and inspiration.

To my wife and her family

To my brother and sisters;

To my uncles and aunts;

To all my family;

As well as all my friends without exception.

I dedicate this work to you . . . .

With my love Abbas.

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synonyme	Description	Unit
Q	Gas flow rate	MMscf/D or bbl/day
Pu	Upstream pressure	psia
Pd	Downstream pressure	psia
ΔP	Pressure drop across choke	psia
Pavg	Average pressure	psia
T	Flowing temperature before choke	°F
S	Choke size	1/64 inch
LGR	Liquid to gas ratio	bbl/MMscf
WT	Water cut (volume percent)	%
GOR	Gas–Oil Ratio	scf/sbbl
AOFP	Absolute Open Flow Potential	MMscf/D
a, b, c, d	Empirical model coefficients	-
γg	Specific gravity of gas	-
x →	Vector of decision variables	-
f(x)	Objective function	-
Ω	Feasible solution space	-
X	Parameter search space	-
m	Number of inequality constraints	-
s	Number of points in the sample population	-
p	Number of complexes	-
m (also used)	Number of points per complex	-
q	Number of points in subcomplex	-
α	Number of offspring generated per evolution	-
β	Number of evolution steps per complex	-
At	Total cross-sectional area of choke	in^2
Ag	Area available for gas flow	in^2
Al	Area available for liquid flow	in^2
NFE	Number of function evaluations	-
RMSE	Root mean square error	-
SCE	Shuffled Complex Evolution	-
α (alpha)	Reflection coefficient (SCE parameter)	-
β (beta)	Contraction coefficient (SCE parameter)	-
γ (gamma)	Expansion coefficient (SCE parameter)	-
δ (delta)	Shrinkage coefficient (SCE parameter)	-
IAE	Individual absolute error	-
ISCE	Improved Shuffled Complex Evolution	-
NP	Number of population	-
N_it	Number of iterations	-
max_s	Maximum number of tests	-
OF	Objective Function	-
STD	Standard deviation	-
ACO	Ant Colony Optimization	-
GA	Genetic Algorithm	-
qg	Gas production rate	Sm3/d

DE	Differential Evolution	-

الملخص

للتنبؤ بمعدلات تدفق الغاز عبر اختناقات رأس البئر في خزانات المكثفات، يجب أخذ عوامل مختلفة في الاعتبار، مثل خصائص خليط الغاز الهيدروكربوني، وتصميم الاختناق ومواصفاته، وظروف الخزان، والتفاعل بين الغاز وسوائل الغاز الطبيعي. يمكن أن يتأثر نظام التدفق وانخفاض الضغط والسلوك العام للنظام بهذه التفاعلات المعقدة، مما يجعل التنبؤ بها أمرًا صعبًا. وقد قام الباحثون والمهندسون بتطوير نماذج رياضية مختلفة وارتباطات تجريبية للتنبؤ بمعدلات تدفق الغاز عبر اختناقات رؤوس الآبار في خزانات المكثفات. غالبًا ما تُستخدم مبادئ ميكانيكا الموائع الأساسية، مثل الحفاظ على الكتلة والطاقة، في هذه النماذج، إلى جانب البيانات التجريبية من القياسات الميدانية. تتطلب النماذج المقترحة عادةً استخراج معلمات ممكنة للمعاملات غير المعروفة. يمكن استخدام طريقة التحسين لتحقيق عملية التحديد هذه. تُعد خوارزمية SCE واحدة من الخوارزميات التطورية الفعالة المستخدمة لحل مشاكل التحسين العالمية في مجالات مختلفة. تحتوي خوارزمية SCE على بنية ثلاثية المستويات تتكون من المستويات التالية: السكانية والمعقدة والبسيطة. ومن ثم، فإن الفلسفة الكامنة وراء خوارزمية SCE هي التعامل مع البحث العالمي باعتباره تطورًا سكانيًا من القاعدة إلى القمة. توضح هذه الدراسة أهمية وقوة هذه التقنية الوصفية. باستخدام مجموعات بيانات حقيقية من آبار مختلفة ونموذجين مختلفين، تمت مقارنة النتائج SCEمع النتائج التي تم التوصل إليها عن طريق خوارزمية ACO وغيرها من ورقة بحثية منشورة مؤخرًا

الكلمات الرئيسية

استخراج المعاملات، التطور المعقد المُختلط التنبؤ بمعدل التدفق • خوارزميات التحسين التطوري • التحسين غير الخطي • حجم الخانق • معدل إنتاج السائل • متغيرات معدل تدفق رأس البئر

ABSTRACT:

To predict gas flow rates through wellhead chokes in condensate reservoirs, various factors must be taken into account, such as the properties of the hydrocarbon gas mixture, choke design and specifications, reservoir conditions, and the interaction between gas and natural gas liquids. The flow regime, pressure drop, and overall system behavior can be influenced by these complex interactions, making it challenging to predict them. Various mathematical models and empirical correlations have been developed by researchers and engineers to predict gas flow rates through wellhead chokes in condensate reservoirs. Fundamental fluid mechanics principles, such as the conservation of mass and energy, are often used in these models, along with empirical data from field measurements. The proposed models usually require a feasible parameter extraction of the unknown coefficients. An optimization method could be used to achieve this identification process. The SCE algorithm is one of the effective evolutionary algorithms used to solve global optimization problems in different domain. The SCE algorithm has a three-tier architecture that consists of the following tiers: population, complex and simplex .Hence, the philosophy behind SCE algorithm is to treat the global search as a bottom-up population evolution. This study shows the importance and strength of this meta-heuristic technique. By using real datasets from different wells and two different models, the findings by using SCE algorithm have been compared with the results reached by means of ACO algorithm and others from a recently published paper

Keywords

Parameter extraction Shuffled complex evolution

Flow-rate prediction · Evolutionary optimization algorithms · Non-linear optimization · Choke size · Liquid production rate · Wellhead flow-rate variables

GENERAL INTRODUCTION

In order to predict gas flow rates through wellhead chokes in condensate reservoirs, various factors must be taken into account, such as the properties of the hydrocarbon gas mixture, choke design and specifications, reservoir conditions, and the interaction between the gas and natural gas liquids. The flow regime, pressure drop, and overall system behavior are influenced by these complex interactions, which make prediction a challenging task. Mathematical models and empirical correlations have been created by researchers and engineers to estimate gas flow rates through wellhead chokes in condensate reservoirs. So in this thesis we'll use application of a shuffled complex evolution algorithm for gas flow rate prediction from gas condensate reservoirs through wellhead chokes. [1]

The SCE algorithm uses a three-tier architecture consisting of the population, complex, and simplex levels. Its core idea is to perform global optimization through a bottom-up evolution process, starting from individual members in the population and building up toward improved solutions.

The primary objective is to extract the unknown parameters of the choke gas flow rate models using a strong identification technique. For these purposes, shuffled complex evolution algorithm SCE has been adopted to validate the parameter estimation.

The purpose of this study is to determine the accuracy of the SCE algorithm in predicting gas flow rates from condensate reservoirs through a wellhead choke. The method's accuracy and reliability will be verified by comparing the results to current models and real data. If it is successful, the SCE algorithm has the potential to enhance decision-making, production planning, and overall efficiency in the petroleum industry [18]

CHAPTER I

I-1 Introduction

Hydrocarbons (oil/gas) are found in underground rock reservoirs. They are produced by wells of various types (vertical, deviated or horizontal, simple or double completion, with also multi-branched wells). The flow characteristics (rate, GOR/CGR, WOR or WC, pressure & temperature) depend on their properties as well as the rock properties. They are generally measured at surface (for instance a well is producing 500 bopd with a GOR of 600 scf/stb, a WC of 20% or a WOR of 0.25, a wellhead pressure of 200 psi and a wellhead temperature of 120 °F). But it is possible to determine from various data the reservoir flow characteristics, for instance the rate in rb/d, the fractional flow of water, the pressure distribution around the well and in the whole reservoir, the flow distribution between layers in multi-layered reservoirs (theoretically & by production logs), and whether we have a single or two-phase HC flow in the reservoir.

In order to efficiently predicting and understanding the fluid mixtures behavior during oil and gas production, an adequate modeling is of crucial importance. Several models could be considered for these purposes, which will be described in this chapter.[1]

During the depletion of a hydrocarbon reservoir, the pressure of the fluid decreases while its temperature remains nearly constant at least as a first approximation. This is because the reservoir rock has a much higher heat capacity than the fluid it contains, helping to maintain the fluid at a stable temperature However, when the fluid flows from the reservoir to the primary separator at the surface, pressure drops occur first in the well and then in the gathering line. These pressure drops are usually accompanied by a decrease in temperature. Even if we ignore heat loss to the surrounding rock, temperature reduction still occurs due to the expansion of the liquid phase (causing partial vaporization) and the Joule-Thomson effect on the vapor phase.

I-2 Classification of hydrocarbon reservoir fluids

I-2-1 Hydrocarbon Reservoirs

A typical pressure-temperature (PT) diagram for a multicomponent hydrocarbon system is shown in. This is commonly known as the phase diagram of the reservoir fluid. Each hydrocarbon accumulation has its own unique phase diagram, which depends solely on the fluid's composition. The type of reservoir is determined by the position of the point representing the initial reservoir pressure and temperature in relation to the phase diagram.

I-2-2 Gas Reservoirs

A reservoir that contains only free gas is called a gas reservoir. It holds a mixture of hydrocarbons that exist entirely in the gaseous state. This gas mixture may be classified as dry gas, wet gas, or condensate gas, depending on its composition and the pressure and temperature conditions of the reservoir.

Either gas reservoirs can experience water influx from an adjacent water-bearing zone, or they can be volumetric, meaning they have no water influx. [2]

I-2-3 Retrograde Gas

A retrograde gas is a type of fluid that can form liquid condensates within the reservoir before reaching the borehole—if proper precautions are not taken. This leads to several drawbacks:

1. Reduced productivity, as the formation of liquid condensates hinders gas flow within the reservoir.
2. Loss of valuable hydrocarbons, since not all condensates can be recovered.

Under reservoir conditions, the temperature of retrograde gas is above the critical temperature but below the cricondentherm, while the pressure is not high enough to keep the fluid above its dew point. As the reservoir pressure drops during production, the pressure-temperature conditions move vertically downward (parallel to the pressure axis) on the phase diagram. This path crosses the dew point curve, causing condensate to form within the reservoir.

Initially, as pressure decreases, the concentration of liquid (condensate) increases. This behavior occurs in a specific area on the phase diagram known as the retrograde zone (typically shaded on diagrams). Below this zone, if pressure continues to fall, the opposite happens the amount of condensate actually decreases.

When reservoir conditions fall into the retrograde zone, liquid forms in the pore spaces of the rock. Unlike gas, this liquid is less mobile and tends to become trapped, meaning a portion of the economically valuable hydrocarbons remains unrecoverable.

To maximize recovery from reservoirs containing retrograde gas, pressure maintenance techniques (either partial or full) must be applied to minimize condensate dropout and ensure better production.

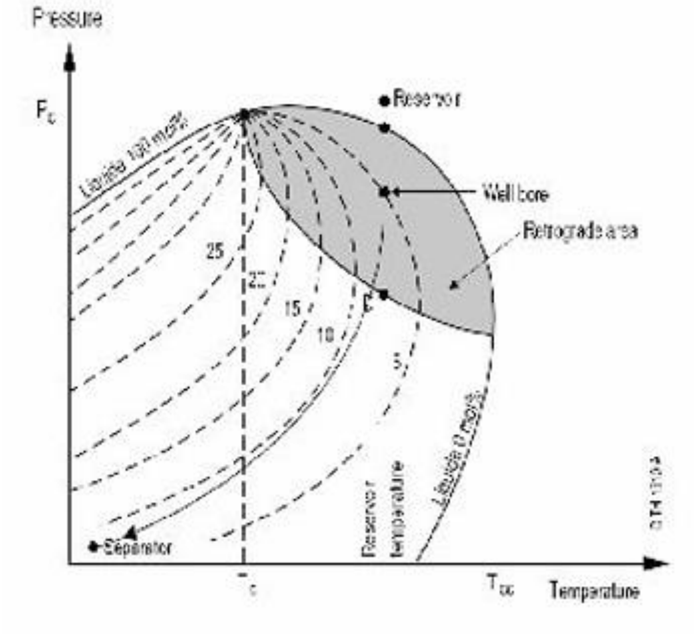

Figure (I.1) Retrograde Gas

I-2-4 Wet Gas or Condensate Gas

A wet gas is a type of fluid that produces liquid condensate between the wellbore and the primary separator, but does not form liquid under reservoir depletion conditions.

This means that the temperature in the reservoir is above the cricondentherm, preventing condensate formation while the fluid remains in the reservoir.

Compared to retrograde gas, wet gas typically contains fewer heavy hydrocarbons, making it less prone to liquid formation under high-pressure conditions.[3]

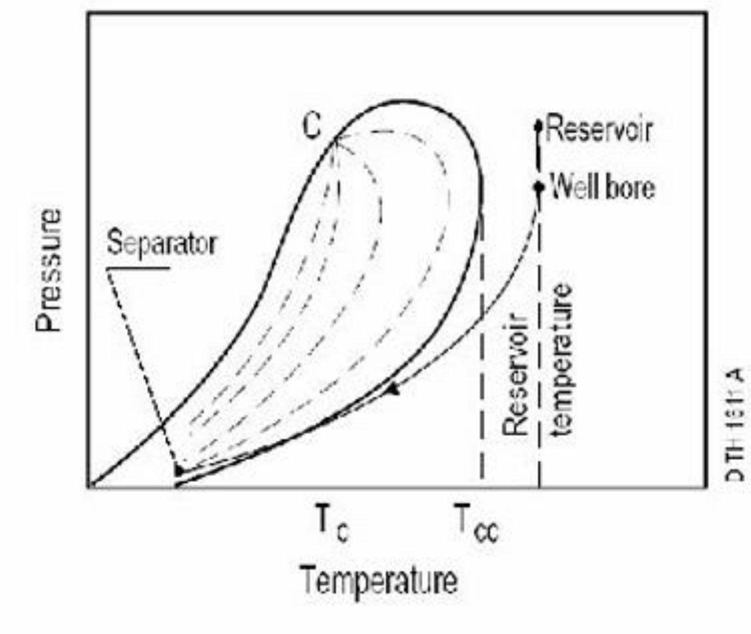

Figure (I.2**) Wet** Gas or Condensate Gas

I-2-5 Dry Gas

A dry gas is a type of fluid that does not produce any liquid, either under reservoir depletion conditions or during transportation from the wellbore to the primary separator.

Its reservoir temperature is typically much higher than the cricondentherm, preventing any phase change into liquid.

In general, dry gas contains very few heavy hydrocarbons, making it the simplest and lightest type of natural gas in terms of composition.

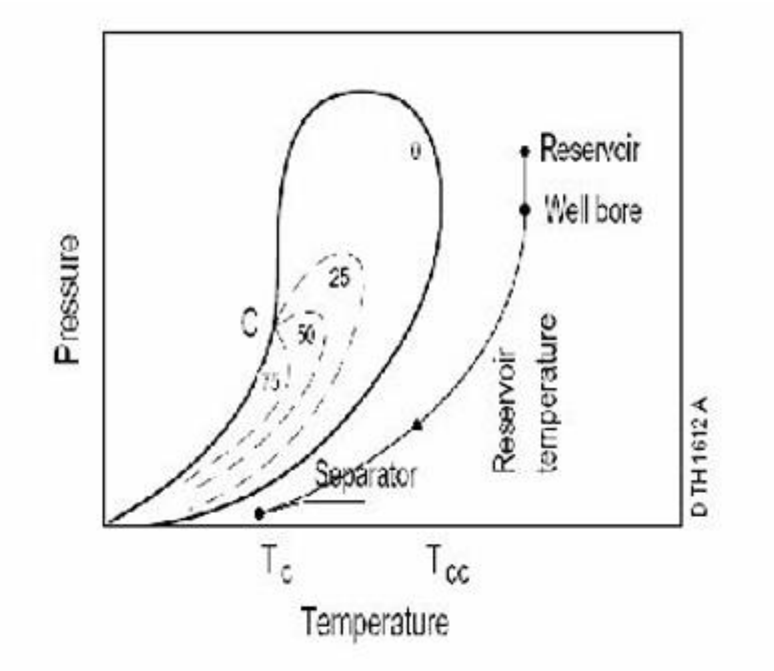

Figure (I.3) Dry Gas

I-3 Flow Regime and well head chokes

The flow through chokes is classified as subcritical or critical (choked) flow. Critical flow occurs when the flow velocity for the fluid reaches its sonic velocity. Pressure waves, caused by the change in pressure, propagate through the flow with the speed of sound. But if the fluid flows faster than the waves can travel, the waves are unable to move upstream, or have any effect on the flow upstream the restriction.

This same evolution can be followed on a P - T diagram representative of the fluid Deposit

I-4 Gas condensate

Chokes are extensively used in Oil and Gas Industry and focused on limit and control mass flow and well potential. Those chokes are nozzles, fixed or adjustable orifices that can control pressure drop and restrict gas volume at certain flowing well head pressure condition. A variety of factors may make it desirable to restrict the production rate from a flowing well, including understanding well potential, prevention of undesirable water

volumes, control reservoir depletion, prevention of coning or sand production, satisfying production rate limits set by regulatory authorities, determine pipe/tank leakage and also for meeting criteria on limitations of rate, velocity, solids volume or pressure drop imposed by surface equipment either maximum operative conditions.[4]

$$\frac{p_d}{p_{up}} = \left(\frac{2}{k+1}\right)^{\frac{k}{k-1}} \qquad \text{(Eq I.1).}$$

$wher$

K: Empirical constants

p_d : Downstream pressure

p_{up}: $Upstream\ pressure$

The passing flow rate is primarily two-phase, and it can produce two types of flow when it passes through flow chokes: critical or sonic flow and sub-critical or sub-sonic flow.

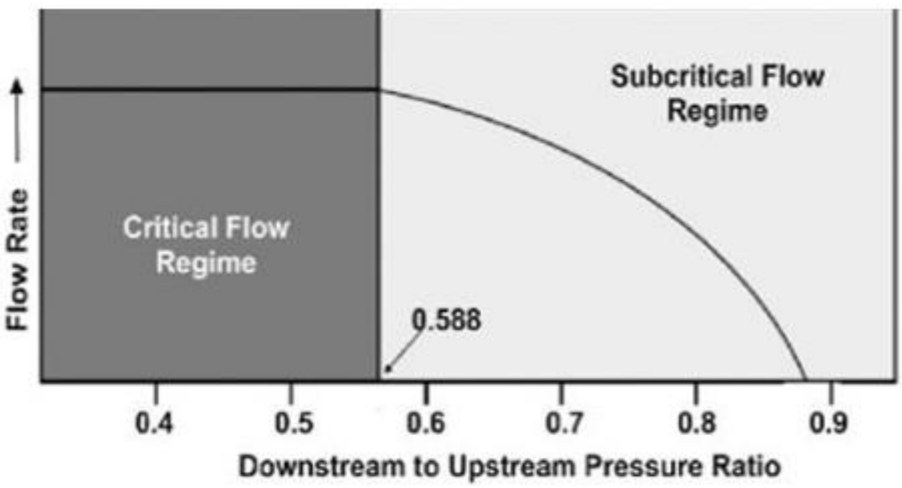

Figure (I.4) Diagram determining critical and subcritical flow in wellhead choke

I-5 Well test

Well test interpretation is the process of obtaining information about a reservoir through examining and analyzing the pressure-transient response caused by a change in production rate. This information is used to make reservoir management decisions. It is important to note that the information obtained from well test interpretation may be qualitative as well as quantitative. Identification of the presence and nature of a no-flow boundary or a down-dip aquifer is just as important as, if not more important than, estimating the distance to the boundary.[5]

I-6 APPLICATION TO GAS RESERVOIRS

Two different types of tests are used for gas wells. Historically, the first testing methods were only designed to define the well deliverability in order to predict the flow rate, as a function of the wellhead pressure. The results were used in the design of the surface production equipment, setting taxes and also for regulating production, particularly in North America. Backpressure tests and isochronal or modified isochronal tests are the usual deliverability testing methods. The theoretical rate at which the well would flow if the sand face was at atmospheric pressure is called the "Absolute Open Flow Potential," AOFP. The analysis of deliverability tests does not yield a description of the well nor of the reservoir.[6]

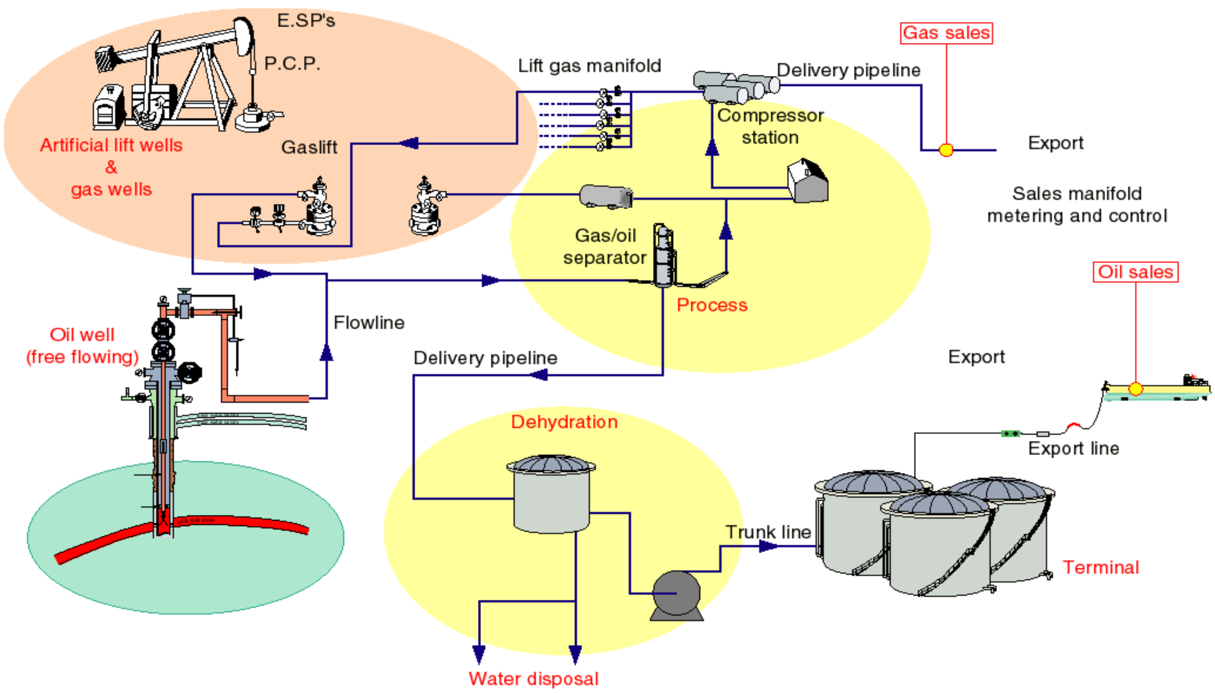

Figure (I.5): The optimized offshore well test process included calculating bottom hole pressure in real time for better predicting reservoir and well behavior.

I-7 Integrated Production System

I-7-1 Multiphase flow

Due to the intrinsic differences in their properties (mainly density and viscosity) the liquid and gas phases in multiphase transport systems cannot move evenly and at the same speed within the lines. Gas and liquid phases can be divided into different flow regimes in the pipeline.[7]

Different approaches have been considered for defining analytical models that can help on determine a solid gas volume prediction of multiphase flow through ckokes. These equations can be classified in many different groups and as result of flow regime, pressure drop and specific understanding on PVT properties. Other set of models can also be extrapolated to critical two-phase flow of wells including solution GOR and better understanding for density mixtures. When gas or gas-liquid mixture flows through a choke, the fluid may be accelerated sufficiently to reach sonic velocity in the throat of the choke. When this condition occurs, the flow is called “critical”, and changes in the pressure downstream of the choke do not affect the flow rate, because pressure disturbances cannot travel upstream faster than the sonic velocity. In petroleum engineering operations, it is commonly assumed that flow through chokes is critical whenever the downstream pressure is less than about half the upstream pressure. Otherwise, the flow is called sub-critical. In the literature, there are a lot of equations that were developed to determine the gas flow rate through chokes for the both flow regimes.[8]

I-8 Multi-phase flow through wellhead chokes Modeling

I-81 Literature review

Multi-phase flow models have been extensively studied and developed over the years to understand the complex behavior of fluids through wellhead chokes. The early contributions include the seminal work of Gilbert in 1954, followed by significant advancements by authors such as Dukler et al. (1964), Hagedorn and Brown (1965) , Beggs and Brill (1973). In the following years, Taitel and Duckler (1976), Ishii and Zuber (1979), and Chen and Golan (1979), Orkiszewski (1983), Yen and Dukler (1986), Zhang et al. (1998), and Abdul-Majeed and Sarica (2004) presented their respective models, contributing to the evolving understanding of multi-phase flow phenomena. Notable models in subsequent years include those by Oliemans et al. (2008), Other influential models were developed by and Hidrobo et al. (2012), and Guo, B (2013), Leal model (2013) , Oliemans et al. Model (2017) , Aider A. Jumaah (2019) , these models have provided valuable insights into the dynamics of multi-phase flow through wellhead chokes, facilitating more accurate predictions and improved optimization strategies in the oil and gas industry.[9]

I-9 Models

I-9-1Gilbert model

The first investigation on gas-liquid two-phase flow through restrictions was performed by Tangren. He presented an analysis of the behavior of an expanding gas-liquid system (1954). He showed that when gas bubbles are added to an incompressible fluid, above a critical flow velocity, the medium becomes incapable of transmitting pressure change upstream against the flow. Several empirical choke flow models have been developed in the past half-century. They generally take the following form for sonic flow

$$p_{up} = \frac{aGLR^{b}Q}{D^{C}} \qquad \text{(Eq I.2).}$$

$wher$

Q : Gas production rate

LGR: Gas– Liquid Ratio

D : choke size

p_{up}: $Upstream\ pressure$

a, b and c are empirical unknown parameters. related to fluid properties.

On the basis of the production data from Ten Section Field in California, Gilbert found the values for a, b and c to be 435, 0.546 and 1.89,respectively .Other values for the constants were proposed different researchers including Baxendell, Ros, and Achong, more than 20 models were developed on the basis of this model.[10]

I-9-2 Seidi and Sayahi

The authors have considered that the passing flow rate through wellhead chokes is a function of wellhead pressure, choke diameter, before choke temperature, and water production rate. A new model for the estimation of the oil rate passing through wellhead chokes has been proposed (2015). In this study, 180 tested data for 5 wells from a heavy crude oil field were used to develop a new model for estimating oil rate passing through wellhead chokes. By considering the Gilbert equation, a New Model is formed as

(Eq I.3).

equation (Eq.I.3):

$$Q_g = aLGR^b S^c \Delta p^d$$

a, b, c and d: Empirical unknown parameters.

The obtained general formula is as follows:

$$Q_g = \frac{0.015S^{1.27} \times \Delta p^{0.56}}{LGR^{0.4}} \quad \text{(Eq I.4).}$$

wher

Qg : Gas production rate

LGR: Gas– Liquid Ratio

Δp : Pressure drop across the choke

The optimum solutions (the best empirical unknown parameters.) achieved for the proposed model and a comparison between measured and predicted gas flow rates of all data pointes The obtained solutions were : 0.0164, 0.3931, 1.2624, and 0.556 for a, b, c, and d, respectively and the new equation turns into the following form:[11]

$$Q_g = \frac{0.0164S^{1.2624} \times \Delta p^{0.556}}{LGR^{0.3931}}$$

wher

Qg : Gas production rate

LGR: Gas– Liquid Ratio

Δp : Pressure drop across the choke

(Eq I.5).

Table (I.1): Different parameter ranges of south Iranian field data.

Parameters	**S (1/64inch)**	**LGR (bbl/MMscf)**	**Qg (MMscf/D)**	**Pu (psia)**	**Pd (psia)**	**DP (psia)**	**T (F)**
Minimum	40	0.688	11.3	1131	824.84	14.5	109
Maximum	192	32.215	113	4452	3045.82	1407	211

Table (I.2): The sub-critical data gathered from South Iranian gas-condensate wells

Number	**Pu(psia)**	**Pd(psia)**	**Qg (MMscf/D)**	**S(1/64inch)**	**LGR(bbl/MMscf)**
1	1501.978	824.83258	11.3008	40	12.4624466
2	1518.076	1484.13896	12.7134	40	9.56457596
3	2422	1740	13.1	40	16.1
4	2103	1726	15.1	40	16.1
5	1827	1638	15.641	40	4.81
6	1406.5	1319.5	19.811715	128	19.5209967
7	1450	1334	23.696365	128	32.214988
8	2741	1798	26.84	40	13.536
9	1827.57	1653.534	27.73	64	5.556
10	2059	2044.5	28.1637125	160	6.14448308
11	1319.5	1290.5	28.711095	144	4.4527821
12	1334	1290.5	28.852355	144	4.80900467
13	1305	1290.5	28.852355	144	4.63089339
14	2016.216	1900.45559	31.7832001	64	5.428
15	1636.156	1195.5025	32.4894934	64	27.491349
16	1493.5	1435.5	33.019525	128	14.9969701
17	3901.499	2944.301	38.72	40	4.374
18	1957.5	1885	38.881815	160	7.35599604
19	1232.5	1218	39.5528	192	2.38847232
20	2102.5	2030	44.14375	160	6.23656662
21	1247	1232.5	44.4969	192	1.2200623
22	1972	1899.5	45.238515	144	7.00867903
23	2073.5	2001	45.521035	160	6.43498259
24	1783.5	1566	45.55635	128	14.8936656
25	1160	1131	45.9095	192	2.13021096
26	1605.094	902.85872	46.5564	40	1.53710038
27	1914	1827	47.67525	144	5.58200765
28	2044.5	2001	50.041355	160	5.70811044
29	1290.5	1276	52.2662	192	1.54066261
30	1131	1102	52.9725	192	1.97632281
31	1145.5	1131	54.3851	192	2.44012459
32	1957.5	1870.5	56.398055	160	7.32749823
33	1885	1566	56.85715	128	13.2710718

34	1986.5	1899.5	56.963095	160	5.64505904
35	2451	1769	57.1043	64	8.193
36	2393	1682	57.5674	64	8.193
37	2393.314	1726.41031	58.2692001	64	8.19319639
38	2480.337	1755.41786	58.2692001	64	8.19319639
39	2407.818	1697.40276	58.2692001	64	8.19319639
40	1624	1551.5	58.5769905	176	5.55555556
41	1348.5	1290.5	60.0355	128	1.92003964
42	1870.5	1537	63.567	128	14.6211553
43	1334	1290.5	63.743575	192	2.12842985
44	1392	1348.5	63.743575	128	1.24677899
45	1174.5	1145.5	64.62645	192	1.92360187
46	1841.5	1667.5	66.74535	128	5.04233045
47	1841.5	1667.5	67.063185	128	5.44308084
48	3785.475	2987.81	77.5	64	4.374
49	1682	1595	82.531155	192	5.18481948
50	1624	1508	83.738928	176	5.58659218
51	1798	1624	83.873125	192	8.50659493
52	3350.385	2016.109	84.4	64	6.3
53	4452.613	3045.822	86.76	64	4.374
54	1783.5	1653	87.5970918	192	6.31938836
55	1740	1595	88.57002	176	5.12052131
56	1595	1508	89.91199	192	4.23904856
57	1595	1566	90.2474825	192	0.688222
58	1493.5	1406.5	95.27987	192	3.41973666
59	1566	1464.5	96.2863475	176	3.87570154
60	1653	1479	101.389365	144	3.96155118
61	1653	1479	101.654228	192	5.03894634
62	1537	1435.5	102.06035	176	3.52660343
63	1653	1493.5	103.8261	176	4.19808297
64	1653	1522.5	104.841406	192	5.68174997
65	1972	1696.5	109.702516	144	5.56669008
66	2175	1899.5	111.295223	144	5.41315815
67	1653	1435.5	113.008	160	5.71381

I-9-3 Kargapour Model

In his 2019 study, Mohammad Ali Karagpur developed a model that applies fundamental principles of fluid mechanics to demonstrate how the flow rate of two-phase fluids through a choke is primarily influenced by the pressure differential across the choke, along with other contributing factors. Based on this analysis, a generalized choke performance equation of the Gilbert type was derived, which explicitly incorporates the differential pressure across the choke. This newly proposed formula was validated using a comprehensive field data set consisting of 399 data points, showing its effectiveness as a semi-analytical tool. The model addresses two specific flow scenarios:

For subsonic single-phase gas flow , the derivation draws upon classical gas flow theory (based on works such as Streeter 1962 and White 2011), incorporating the concept of gas mass flow rate and applying average values for key gas properties. Additionally, the model uses the idea of a discharge coefficient, commonly applied in orifice metering, to account for flow restrictions. As a result, a simplified yet accurate expression for predicting gas flow rate under subsonic conditions is obtained.[12]

$$q_{SCFD} = 65554 \times D^2 P_{UP} \sqrt{\left(\frac{P_d}{P_{UP}}\right)^{1.5625} \left[1 - \left(\frac{P_d}{P_{UP}}\right)^{0.21875}\right]}$$

$wher$

q : Gas production rate

Pd : Downstream pressure

D : choke size

p_{up}: $Upstream\ pressure$ (Eq I.6).

Choke for two-phase (gas and liquid) it is assumed that part of area of choke is occupied by gas stream and liquid flows in the rest. In mathematical form At = Ag + Al , it is written: where 'At ', 'Ag', and 'Al' are total cross-sectional area of choke, assumed area available for gas flow, and assumed area available for liquid flow, respectively. By utilizing Bernoulli's equation for liquid flow and Eq(4)

One phase) for gas flow and substituting them in Eq. (two phase), the following equation is generated as a general form of choke formula for estimating the liquid flow rate in two-phase fluid flow:[13]

$$Q_{BPD} = P_{UP} D^2 \times \left\{ \frac{\sqrt{P_{UP}}}{552 \times \sqrt{\frac{\left(1 - \frac{P_d}{P_{UP}}\right)}{SpGr}}} + \frac{GOR}{65554 \times \sqrt{\left(\frac{P_d}{P_{UP}}\right)^{1.5625} \left[1 - \left(\frac{P_d}{P_{UP}}\right)^{0.21875}\right]}} \right\}^{-1}$$

$wher$

Q : Liquid production rate

Pd : Downstream pressure

D : choke size

p_{up}: $Upstream\ pressure$

GOR : Gas–Oil Ratio

(Eq I.6).

I-9-4 Leal model

The equation expresses the gas flow rate from the wellhead choke in terms of choke diameter, gas specific gravity, flowing fluid temperature, upstream pressure and downstream pressure(2013). The Leal equation is used as the objective function for analysis is presented here as equation:

$$Q_g = \beta_1 D^{\beta_2} \left(\frac{P_{UP}}{14.7}\right) \sqrt{\left(\frac{1}{\gamma_g T}\right)}\ \beta_3 \left[\left(\frac{P_d}{P_{UP}}\right)^{\beta_4} - \left(\frac{P_d}{P_{UP}}\right)^{\beta_5}\right] \quad \text{(Eq I.6).}$$

$\beta_1$to β_5 are unknown parameters.

Where, Leal presented values ideal of constants as follows :[14]

β_1 = 0.00149228 β_2 = 2.118654173 β_3 = 1.586085251 β_4 = 0.739034 β_5= 1.369516866

I-9-5 Aider A. Jumaah

Gilbert correlation has been modified to determine the performance of multiphase fluid-flow through the wellhead and choke. The modification present two sets of new correlations based on statistical analysis of 33 production tests data from 12 wells produce from Tertiary Reservoir in Khabaz oil field, first correlation is modified of Gilbert equation to predict liquid flow rates as a function of wellhead flowing pressure, gas-liquid ratio and choke size, the second correlation takes the effect of water cut and sediment (BS & W) as an effective parameter to minimize error. A comparison between the results of each correlation with measured date has been made to select the best correlation to predict flow rate in newly drilled wells (2019). The oil flow rates predicted by the new correlations show excellent agreement with the measured rates and the second modified Gilbert correlation are found to be closest to all ranges of flow rate variables with an average error of 10 % and R2=0.9493[15]

I-10 Area of study

The Khabaz oil field is multi-pay zones Carbonate oil fields like most of the carbonate oil fields in the north of Iraqi. It is located in North West of Kirkuk city and far about 12 km from Kirkuk city center as shown in Figure (I.4).

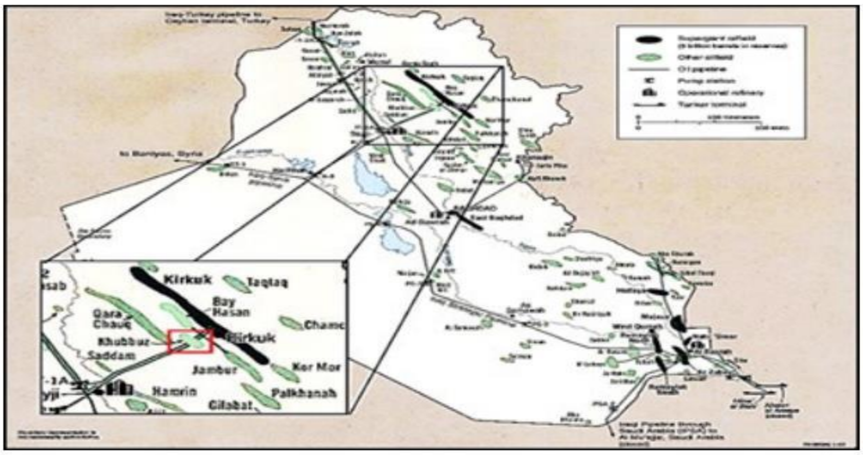

Figure (I.6): Khabaz oil filed location

The Khabaz oil field consists of three main hydrocarbon reservoirs.

- Tertiary Reservoir.
- Cretaceous Upper Qamchuqa (Mauddud) Reservoir.
- Cretaceous Lower Qamchuqa (Shuaiba) Reservoir[16]

Table (I.3): Production Test Data

No	DATE	Chock size in	Pressure psi	Q bbl/d	GOR scf/bbl	WT %	flow path
1	15/07/2000	0.438	446.5	1000	1112	1	Tubing
2	05/05/2002	0.375	445	850	873	0.5	Tubing
3	22/07/2000	0.375	1102	1300	913	1.3	Tubing
4	01/05/2002	0.375	1233	1150	1290	2.3	Tubing
5	03/09/2000	0.250	1711	400	2595	0	Tubing
6	16/10/2001	0.313	1377.5	450	1976	0	Tubing
7	17/08/2002	0.250	1850	400	2500	0	Tubing
10	15/10/2001	0.375	1116.5	1600	927	4.5	Tubing
11	04/05/2002	0.375	1130	1250	949	4.7	Tubing
12	18/07/2000	0.375	1203.5	1200	1174	0.2	Tubing
13	21/07/2000	0.313	1232.5	850	1221	0.3	Tubing
14	05/09/2001	0.313	1261.5	1100	1078	0.9	Tubing
15	20/10/2001	0.250	1305	750	989	0.8	Tubing
16	10/10/2001	0.563	1102	2600	1027	1.2	Tub.
17	07/07/2000	0.250	1450	500	1780	0	Tubing

18	10/05/2002	0.250	1855	450	1976	0	Tubing
19	16/07/2000	0.500	1160	2250	1121	0	Tubing
20	20/07/2000	0.438	1189	1700	1047	0	Tubing
22	21/05/2002	0.438	1090	1700	1134	0	Tubing
23	04/08/2002	0.500	1190	2200	1079	0	Tubing
24	27/10/2001	0.375	1276	1100	1483	0	Tubing
25	08/05/2002	0.375	1275	1000	1483	0	Tubing
26	29/06/2000	0.656	783	2900	921	0	Tubing
27	01/07/2000	0.563	899	2150	966	0	Tubing
28	03/07/2000	0.500	928	1550	957	0	Tubing
29	23/10/2001	0.250	1363	650	1369	0	Tubing
30	24/08/2002	0.250	1025	700	847	0	Tubing
31	23/07/2000	0.297	1232.5	950	1249	0.8	Tubing
32	17/09/2001	0.297	1322	1250	1068	0	Tubing
33	22/10/2001	0.266	1421	850	1134	0	Tubing

The first correlation for Khabaz field is Gilbert modified equation based on regression analysis of equation (Eq.I.7) as flowing:

$$Q = PWF \frac{D^a}{c \times GOR^b} \qquad \text{(Eq I.7).}$$

a, b and c : Empirical unknown parameters.

The second correlation has been developed considering a parameter which has not been covered in the previous correlations; water cut (Wct) measured volume percentage of the production stream, in addition to other parameters which had been added to the correlation, in order to reduce error in the field condition to a minimum, as represented in the following form.

$$Q = PWF \frac{D^a}{c \times GOR^b} \times \left(1 - \frac{W_{CT}}{100}\right) d \qquad \text{(Eq I.8).}$$

When they use 33 test data of production are gathered from 12 wells in Table (I.1):

The first correlation:

a = 1.7634, b = 0.9058, c = 0.000275

The second correlation:

a = 1.733, b = 1.159, c =0.0000486 and d= 1.3936[17]

I-11 Conclusion

This chapter has explored the modeling of multiphase flow through wellhead chokes, highlighting its vital role in accurately predicting fluid behavior during oil and gas production. These models integrate variables such as fluid characteristics, flow rates, choke design, and external conditions to simulate flow dynamics and associated pressure losses. Through the use of sophisticated mathematical and computational tools, such modeling contributes to optimizing production, enhancing operational safety, and supporting informed decision-making. Nonetheless, accurate parameter estimation remains essential for achieving reliable model performance. Hence, selecting a suitable optimization algorithm becomes critical to improving the overall modeling process. The following chapter will delve into various optimization methods that can be employed to effectively determine the unknown parameters within the model.

CHAPTER II

CHAPTER II: OPTIMIZATION METHOD

I. CHAPTER II: OPTIMIZATION METHOD

II-1 Introduction

Reservoir engineering problems (e.g., history matching, production optimization, and improved recovery) are nonlinear, high-dimensional parameter estimation with complex physical constraints. Automatic calibration of reservoir simulation models (history matching) or the optimization of well/field operation strategies is thus a global optimization problem. Trial-and-error or classical gradient-based methods can easily get trapped in local optima or require derivative information that is difficult to obtain for complex flow models. Hence, derivative-free, global optimization algorithms (i.e., genetic algorithms, particle swarm, simulated annealing) have been attempted in reservoir engineering to handle nonlinear, multimodal search spaces (Wang, 1991; Holland, 1992). Among them, the Shuffled Complex Evolution – University of Arizona (SCE-UA) algorithm has emerged as an effective method originally developed for watershed model calibration. Originally applied in the field of hydrology, the hybrid evolutionary strategy it embodies is also directly applicable to reservoir problems that involve reservoirs with multiple regions of attraction, non-continuous objective functions, and extremely non-convex surfaces. Below, we present an overview of the SCE-UA algorithm and illustrate its application in the prediction of gas flow rates from condensate reservoirs with wellhead chokes. [18]

II-2 Shuffled Complex Evolution Algorithm

The Shuffled Complex Evolution Algorithm (SCE) algorithm is a global optimization method that is based on a population approach, combining aspects of random sampling, clustering, and local search methods based on simplex methods. The algorithm was first suggested by Duan, Gupta, and Sorooshian (1993) with the aim of allowing automatic calibration of rainfall-runoff models. The basic concept is to maintain multiple subpopulations, called complexes, that search the parameter space simultaneously and occasionally share information to avoid premature convergence. Basically, SCE combines four established notions in optimization:

• Random and Deterministic Search: It combines stochastic sampling of the search space with systematic downhill simplex movements to balance exploration and exploitation.

• Clustering: The aggregation of sample points is segmented into complexes according to fitness hierarchy, facilitating concentrated local exploration within each cluster.

• Competitive Evolution: In each complex, candidate solutions (parents) compete to generate offspring via Nelder–Mead simplex operations (reflection, contraction, etc.). Better solutions have higher chance to contribute (triangular probability weighting)

• Periodic Shuffling: After evolving each complex for a certain number of steps, all the points are mixed together and re-divided into new complexes, which mix information globally this shuffling exchanges information of good regions among complexes and maintains diversity

SCE has good global convergence behavior over a variety of problems. By incorporating Nelder–Mead simplex moves, which do not need gradient information, within a multi-complex paradigm, SCE effectively navigates challenging, multi-modal landscapes. Empirical research demonstrates SCE to be superior to numerous previous approaches (e.g., simplex multistart, genetic algorithms, adaptive random search) for solving challenging calibration problems. For example, Muttil and Jayawardena (2008) report SCE "has been used extensively and proved to be a robust and efficient global optimization method" for conceptual model calibration. These advantageous features (no derivative requirements; adept exploration and exploitation skills) render SCE particularly appealing for complicated reservoir issues.[19]

II-3 Shuffled Complex Evolution Steps

The SCE procedure can be broken down into the following main steps

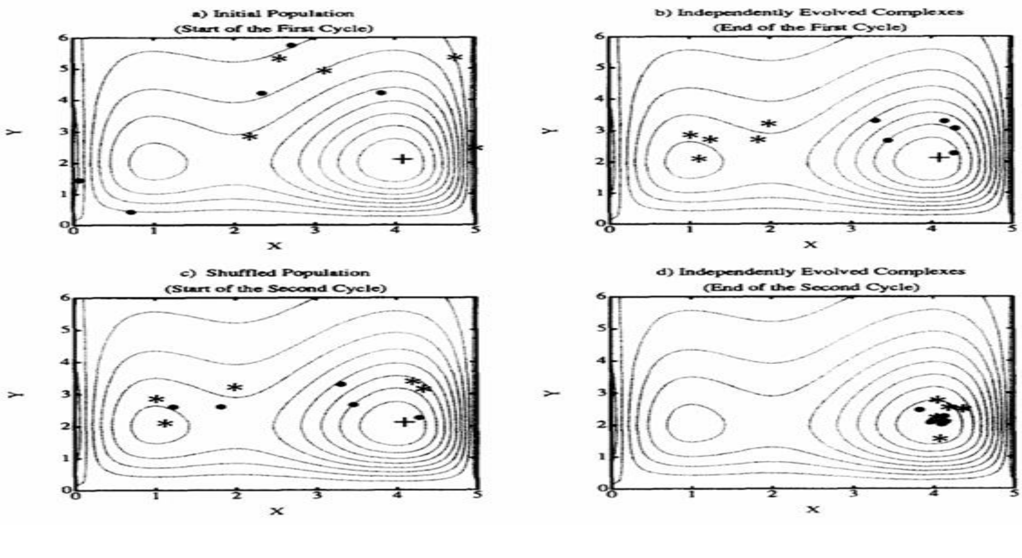

Figure (II.1): Illustration of the shuffled complex evolution (SCE) method

II-3-1 Generate Initial Population (Sampling): Choose randomly s points in the possible parameter space (e.g., through uniform sampling) and compute the objective function (criterion) at each of the s points chosen. In practical applications, the value s can be several orders higher than the number of unknown parameters. The random initialization guarantees an unbiased global representation under situations where prior knowledge is unavailable.

II-3-2 Rank Points: Sort the s points by increasing objective value (assuming minimization) The best point has index 1 and worst is s Ranking facilitates partitioning and selection.

II-3-3 Partition into complexes: split the s points into p complexes, with m points in each complex. The complexes are split such that the first complex contains every p(k – 1) + 1 ranked point, the second complex contains every p(k – 1) + 2 ranked point, and so on, where k = 1,2……. M.

II-3-4 Evolve Each Complex (Competitive Complex Evolution): Within each complex A_k, perform several evolution steps (CCE) to improve solutions The CCE procedure (essentially a local simplex search) works as follows:

- Subcomplex Selection: Repeatedly select a small subcomplex of q points from A_k (often q=2q=2q=2 or a bit larger) using a triangular probability that favors lower (better) ranked points
- Generate Offspring: Perform Nelder–Mead operations: calculate the centroid of the best q−1q-1q−1 points, reflect worst point over centroid, and optionally contract or randomly mutate if necessary. Each offspring point is scored, and it replaces worst of subcomplex if it is an improvement. The process of reflection/contraction/mutation continues a times in order to create α offspring off the subcomplex. After these α steps, the new subcomplex (parents and new offspring) is merged again into A_k, and A_k is sorted again by objective value.
- Repeat Evolution Cycles: Steps 1–6 are reiterated, and the entire CCE cycle is reiterated β times for each complex (i.e. each complex "evolves" β generations). Briefly, each complex performs β evolutions, each using α offspring generation steps from chosen subcomplexes.[20]

II-3-5 Shuffle Complexes: Once all complexes have been evolved for β steps, recombine the populations: gather all S points from evolved complexes, rank by objective, and redistribute into P new complexes (as in Step 3). Shuffling provides information exchange between complexes: good solutions discovered in one complex can seed others. It enhances global exploration by merging the search communities.

II-3-6 Check Convergence: Assess the convergence criteria. Typical criteria are: minimum significant improvement in the best objective over a number of shuffles, small objective function variability among all the points, or achievement of a pre-specified maximum number of function evaluations. If convergence, report current optimal solution; otherwise, return to Step 4 with the new complexes. In addition, SCE-UA can automatically decrease the number of complexes in the event of stagnation of convergence (by combining the poorest complexes).

The SCE is widely used primarily because of the following reasons: The algorithm is easy to comprehend and be executed via coding; Many elements of the Algorithms such as the formation of complexes and the evolution of complexes are parallelizable, as is suitable for parallel computing when optimizing large and complex issues (Kanetal.,2016); Only the amount of complexes must be adjusted by users when taking there commended the values of the alternative parameters (Duan et al., 1994), and these Recommendations have survived through different eras; The algorithm has proven to be more efficient and robust than some classic algorithms like the genetic algorithm (GA), the simulated annealing algorithm (SAA) ,and the differential evolution algorithm (DE) to resolve certain problems in the field of hydrology and water resources by some researches (Cooper et al., 1997; Arsenault et al., 2014).[21]

II-4 The Shuffled Complex Evolution Algorithm Adaptive

Tessema and Yen (2009) suggested the adaptive penalty function in SCEA. The function can adaptively regulate the penalty coefficient based on the feasible ratio of the current population, the ratio of feasible individuals, to manage the severity of the penalty. It was initially integrated into genetic algorithms. to solve constrained optimization problems, and obtained good performance on 22 benchmark functions. Lee and Kang (2016) incorporated this adaptive penalty function into the SCE-UA and introduced the SCEA. Optimization problems with inequality constraints can typically be stated as:

$$\text{Minimize } f(x)$$

$$snbject\ to\ g_j\ (\vec{x}\ ) < 0, \mathrm{j} = 1, \ldots\ldots, \mathrm{m}$$

$$\vec{x} \in X$$

where n is the number of decision variables, $\vec{x} = (x_1, x_2, \ldots, x_n)$; m is the number of inequality constraints; and X is the search space composed of the upper and lower boundaries of each decision variable. The region in X that satisfies all inequality constraints is the feasible region Ω.[21]

Procedure for the SCEA Algorithm

Begin

  Randomly generate initial population $\vec{x}_i$ $\forall i$, i=1, …, Population_Size

  For G=1 to Maximum_Iteration **Do**

    For i=1 to Population_Size **Do**

      Evaluate $f(\vec{x}_i)^G$

      Evaluate $v(\vec{x}_i)^G$

    End For

    Find r^G

    If $r^G \neq 0$ **then**

      $f_{min}{}^G \leftarrow \min\{f(\vec{x})^G\}$

      $f_{max}{}^G \leftarrow \max\{f(\vec{x})^G\}$

    End If

    For i=0 to Population_Size **Do**

      Evaluate $F(\vec{x}_i)^G$

    End For

    Perform SCE-UA operators

    Update population

    $G \leftarrow G + 1$

  End For

End

Figure (II.2): Pseudo code of the SCEA

the adaptive penalty function method is embedded into the SCE-UA in the form of a subroutine

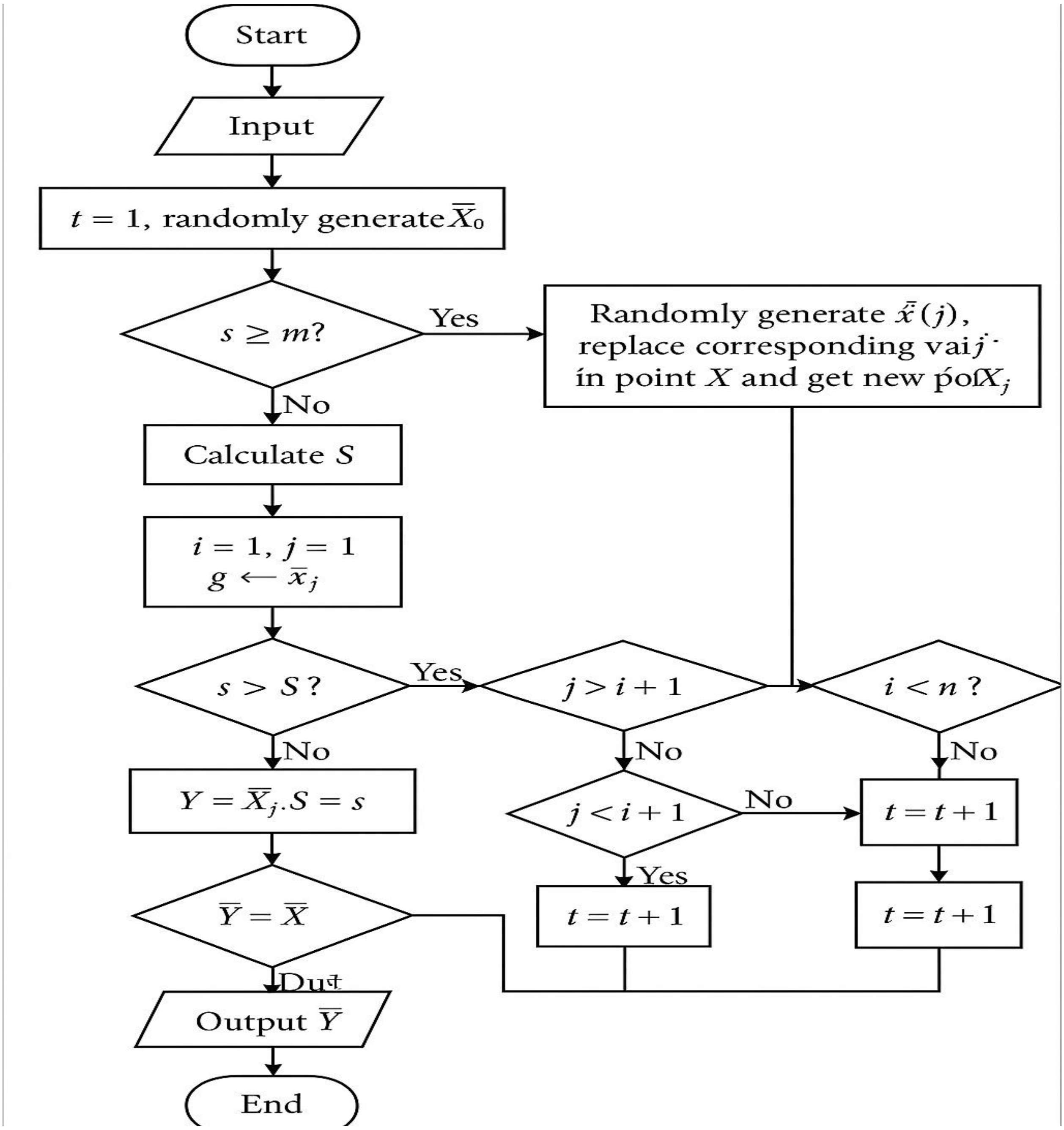

Figure (II.3): Flow chart of the initial feasible point search strategy.

CHAPTER II: OPTIMIZATION METHOD

II-5 competitive complex evolution:

The SCE possesses two components for the generation and updating of points: 1. initialization of starting points, and 2. competitive complex evolution (CCE) algorithm. Correspondingly, the two components were revised so that all the new generated points were within the feasible space. Meanwhile, the enhanced simplex search approach suggested by Muttil and Jayawardena (2008) was used to increase search efficiency. The remaining steps of the CSCE are identical to those of the SCE.[22]

X is the region outlined by the upper and lower limits of each decision variable. The objective of the initial feasible point search is to search through space X in an attempt to reach a point in the feasible region Ω. For most practical problems, the feasible region is usually not very small, random searching by computer suffices to obtain an initial feasible point, and the use of a complex algorithm will prolong the running time of the program instead. However, for problems with high dimensions and complex constraints, this method will be time-consuming. Thus, the fast and effective identification of initial feasible points that satisfy the imposed constraints is a difficult issue in the field of optimization. We employed a process close to the univariate search approach (Liu et al., 2001) for creating the initial feasible points. $\vec{x}$ = (x1, x2,. ., xn) is a vector of decision variables; a→= (a1, a2, ., an) and b→= (b1, b2,...., bn) represent the lower and upper boundaries of each variable respectively; S represents how many constraints $\vec{x}$ can satisfy, and it is the guidance of searching, the point meeting more constraints will be retained as a new basic point for searching to approach the feasible region. If $\vec{x}$ is feasible, S=m; Q is the maximum number of adjustments in each dimension, and its default value is 10; L is the maximum number of adjustments based on a starting point, and the default value is four; and Y→= (y1, y2,. ., yn) is the retention point. Q and L only affect the search time, and users according to specific problems if necessary can adjust them. We're utilizing their default values here. Search steps are as follows :

Step 1: Choose an arbitrary starting point →x0 at random in space X, calculate S, and set S1=S and Y→=$\vec{x}$ 0. If S1=m, get the feasible point, print Y→, and end the algorithm ; otherwise proceed to step 2.

Step 2 : Scale relative to Y→. Fix x2,…, xn and scale Y→in the x1-direction. →e1 = (1, 0, 0,., 0), randomly select x1 in [a1, b1], new point →x1 = Y→+ (x1 − y1 →e1, calculate S

1. If S=m, find the feasible point, output $\vec{x}$, and stop the algorithm.
2. If S1 < S < m, find the better point, set S1= S, and set $\vec{y}$ = →x1. Go back to step 3
3. If S ≤ S1, go back to step 2. If no better point or feasible point is obtained after Q adjustments in the $\vec{x}$ 1-axis direction, proceed to step 3.

Step 3: Perform operations similar to those performed in step 2 along the directions of the x2,…, xn axes in turn, thus completing one cycle of adjustments. If no feasible point is found, go back to step 2 to start a new cycle of adjustments. If after L cycles of adjustments no feasible point is found, go back to step 1 to obtain a new initial point, denoted by →x0, and repeat the process until a feasible point is found.

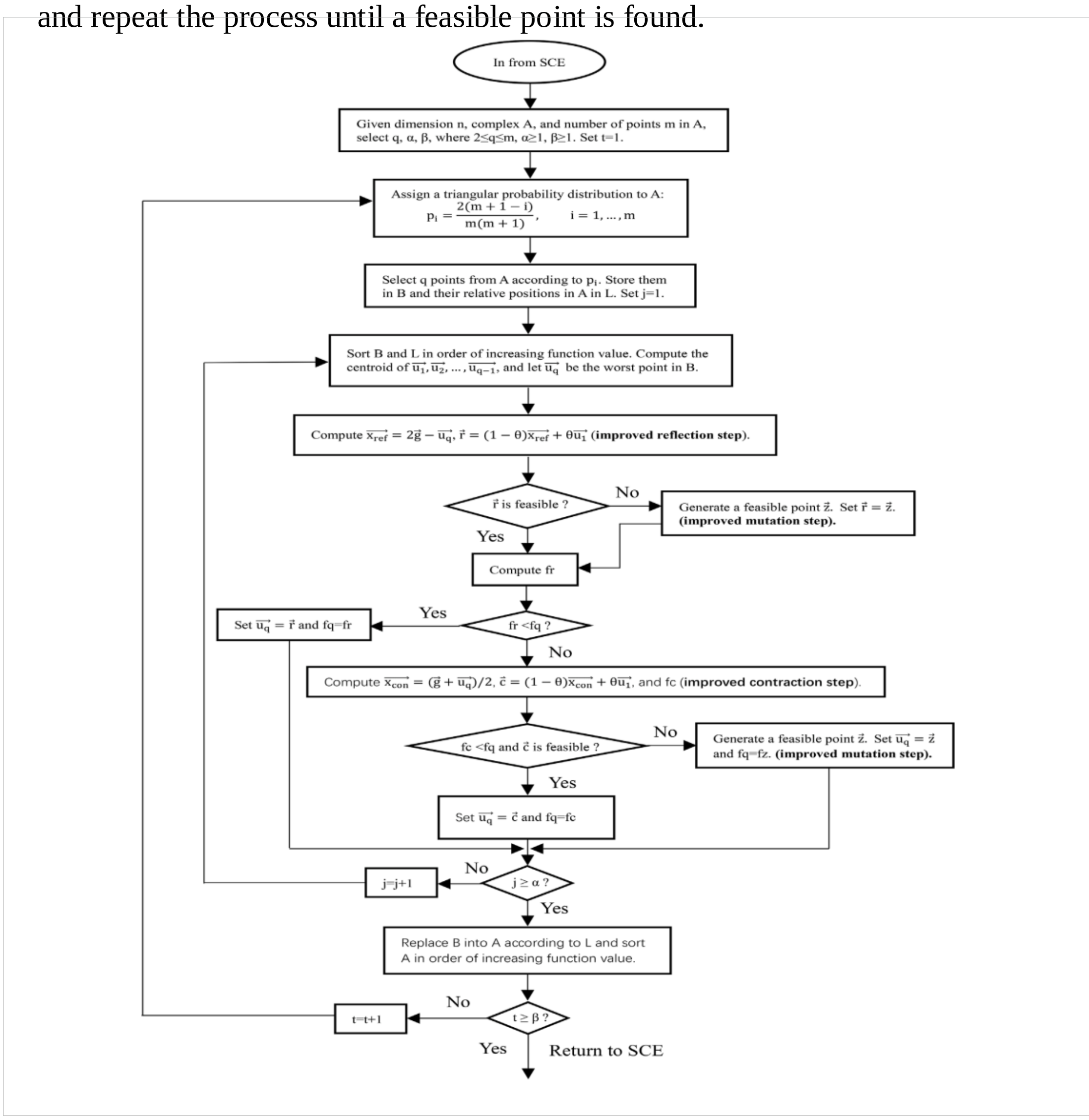

Figure (II.4): Flow chart of the improved CCE algorithm.

By applying the above algorithm s times, s initial feasible points are generated. The flow chart of this search strategy is shown in Fig 4.[23]

II-6 Basic Qualities

Demographic Grouping and Clustering: Utilizing a population of size s divided into p complexes, SCE-UA performs a number of parallel searches. Each complex tends to span the parameter space (due to rank-based partitioning), so the search of each complex is quite insensitive to local irregularities.

Nelder–Mead Local Search: Nelder–Mead simplex steps (reflection, contraction, mutation) allow a complex to converge efficiently to local minima without requiring gradients This makes SCE-UA robust on non-smooth or noisy surfaces. Competitive Selection: In each complex, the employment of a triangular probability (best point more apt to be selected) guarantees that superior solutions lead the search

This contest (based on genetic algorithms) combines exploitation of good solutions and exploration by permitting worse points to be replaced by random draws from time to time.[24]

Mixing Shuffles: Following the evolution of subpopulations, the shuffle phase compels each complex to accept new genetic information from the global population. It can be intuitively understood that populations "share" information they have learned about the search space. As Duan et al. (1993) note, this enables various regions (local minima) to be searched by each complex and enhances the likelihood of the global optimum being located.

SCE-UA's hybrid character, in which global random search is combined with directed simplex steps, tends to result in improved global convergence compared to methods based exclusively on local or random mechanisms. Indeed, research by Duan et al. (1993) demonstrated that, for a given number of function evaluations, SCE-UA has a greater likelihood of locating the global optimum than certain previous approaches. Its structure is especially well adapted to problems featuring numerous local optima or distorted objective landscapes, circumstances that are prevalent in reservoir calibration applications.[25]

II-7 Applicability to Gas Flow Prediction in Condensate Wells

Gas condensate reservoirs and wellhead choke flow are multiphase, nonlinear. Gas flow through a choke is choked (critical) or subcritical, depending on the upstream conditions. In critical flow, the mass rate changes almost completely as a function of upstream fluid properties and pressure, but in subcritical flow, it is a function of both downstream and upstream conditions. Empirical and semi-empirical choke correlations (e.g. by Tangeren, Gilbert, Boxendahl, Ros, Poettmann-Beck, etc.) have be (Eq.II.1) m data but are often single-phase or oil-water correlations and will not cover condensate wells. Engineers fit multiphase correlations of the form:

$$\mathrm{Q} = \mathrm{c}\frac{(\Delta p)^{\alpha}}{p_{avg}^{b}}$$

Where Q is flow rate, ΔP is pressure drop (or upstream pressure), P avg is average pressure, and a,b,c are empirically determined coefficients Determining these coefficients typically requires regression on field measurements. However, condensate wells often exhibit retrograde condensation and two-phase flow phenomena, making the correlations highly nonlinear and parameter-sensitive. Traditional estimation (linear regression on log-transformed data, for example) may not capture the true physics, and manual tuning can be biased by initial guesses [26]

This is where SCE can help: we can formulate a calibration problem to fit a choke-flow model to field data. For a given well, assume we measure upstream pressure p_{up}, downstream pressure p_d, gas gravity emperature, etc., and obtain observed gas flow rates $Q_{obs,i}$ at different choke settings. We select a predictive model Q_{pred} (θ) parameterized by unknown vector θ (e.g. θ=[c,a,b,…]). Then define an objective (loss) function, for instance the sum of squared relative errors:

$$\emptyset(\theta) = \sum_{i=1}^{n}\left(\frac{Q_{pred,i}(\emptyset) - Q_{obs,i}}{Q_{perd,i}}\right)^2 \qquad \text{(Eq.II.2)}$$

This objective is generally nonlinear and multimodal in θ, especially if Q_{pred} involves complex multiphase physics. SCE can be used to minimize Φ (θ) by treating the correlation coefficients as decision variables within specified bounds (e.g., coefficients positive, exponents within physical limits).[27]

II-8 Importance to Nonlinear Multidimensional Flows

Major reasons SCE is well adapted to this application are:

Multiple Local Optima: Different sets of parameters in choke models can lead to similar flows, which creates local minima of fitting error. SCE multi-complex search reduces the chance of being trapped in a suboptimal basin

High-Dimensionality: When the model has many parameters (gas compressibility factors, liquid holdup corrections, exponent terms, etc.), the search space is high-dimensional. SCE structures and adapts a large population (s) spanning the space, thereby facilitating the exploration of multi-dimensional landscapes.

Non-Smoothness: Choke models may exhibit discontinuities (e.g., between regimes of choke flow) or thresholds (e.g., the onset of condensation). The Nelder–Mead-based search mechanism is highly capable of coping with such nonsmooth surfaces.

Absence of Gradients: It is often difficult to derive analytic gradients of the choke model with respect to its parameters, especially when the model is a black-box simulator. The SCE algorithm only requires objective function evaluations, making it derivative-free and, as such, directly applicable.

In summary, predicting gas flow across chokes in condensate wells is a difficult, multi-dimensional calibration problem. The ability of SCE to provide global/local search, along with its diversity of population, makes it a good candidate for this kind of optimization task. The algorithm can simultaneously adjust multiple empirical parameters so that it attains balance between low flow and high flow conditions.[28]

II-9 Advantages of SCE in Gas Flow Prediction

Global Search and Robustness: SCE has the ability to escape local minima and converge towards global optima with high probability This is helpful in choke calibration because the error surface may be multimodal (i.e. two vastly different sets of parameters giving a similar fit).

Efficiency on Complex Surfaces: The application of Nelder–Mead simplex in every complex renders local convergence efficient even on complicated surfaces SCE employs curvature information (implicitly via simplex geometry) to move down valleys, which simple random search does not have.

Population Diversity and Exploration: The population-based nature (multiple complexes and shuffling) preserves diversity. The early generations are free to explore widely, preventing premature convergence

Derivative-Free and Flexible: No need for gradient or special structure: any black-box choke model or even machine-learning surrogate can be employed with SCE and calibrated. It can handle discrete or noisy variables as well.

These advantages position SCE as a top candidate when classical methods (e.g. trial-and-error, gradient descent) are overwhelmed by nonlinearity and multiple objectives. In reservoir engineering, SCE (and its variants) have seen widespread application in calibration and uncertainty analysis (e.g. SCEM for Bayesian inference) already. Application to choke flow prediction comes naturally as another parameter-fitting problem with difficult physics.[29]

II-10 Limitations and Considerations

Computational Cost: SCE can be extremely expensive in terms of objective evaluations (function calls) as it maintains and evolves multiple complexes. If the choke model itself is computationally expensive to evaluate (e.g., a high-resolution two-phase flow simulator), then the expense may be high. Choke correlations, however, are cheap analytic functions, so the expense of SCE is relatively low here. Parallel computation can also speed up by evolving complexes in parallel.

SCE has its own hyperparameters (s,p,q,a,β). Performance is dependent on these. Some guidelines are given by Duan et al. (1994) but some trial runs will be necessary to tune them to work optimally for a problem.

No Global Optimum Guarantee: Like any heuristic, SCE cannot guarantee the identification of the true global optimum in finite time. It usually produces a very good solution, but multiple runs or hybridization can be used to validate results.

Constraint Handling: SCE is unconstrained in its nature (only handles bounds). All physical constraints (e.g. a parameter must be integer or satisfy a nonlinear inequality constraint) must be handled through penalties or transformations, which may complicate implementation.

Despite these doubts, in many of the optimization problems involving reservoir engineering – like choke flow calibration – the benefits often outweigh the related costs, especially given the intricacy of the problem.[30]

Table(II.1): Summary of research on SCE

Article	Technique introduced	Dimensional sizes	Results	Merits	Limitations
Duan, Q., Sorooshian, S., & Gupta, V. K. (1992)	The Shuffled Complex Evolution (SCE) algorithm was introduced as a global optimization method. It combines concepts from the genetic algorithm and competitive evolution to improve convergence speed and robustness in optimizing hydrological model parameters.	numParams = 5 numComplexes = 4 beta = 0.6 , alpha = 1.2	Random search and alternative methods like SCE were shown to outperform grid search in terms of computational efficiency and finding optimal hyperparameters in high-dimensional spaces.	High efficiency in finding global optima. Robustness in handling multi-dimensional and non-linear optimization problems. Applicability to various hydrological models.	Computationally expensive for high-dimensional problems. Requires careful selection of the number of complexes and other hyperparameters to balance exploration and exploitation.
Bergstra, J., & Bengio, Y. (2012)	Though the paper focuses on random search for hyperparameter optimization, the SCE algorithm is mentioned as an alternative technique that could be applied for tuning machine learning models. SCE's competitive evolution strategy could address the inefficiencies of grid and random search.	numParams = 3 numComplexes = 2 beta = 0.5 , alpha = 1.5	Random search and alternative methods like SCE were shown to outperform grid search in terms of computational efficiency and finding optimal hyperparameters in high-dimensional spaces.	The SCE algorithm offers a structured way to explore the hyperparameter space, making it more efficient than pure random search. Suitable for small to medium-sized hyperparameter tuning problems.	Not as fast as purely random search for fewer dimensions. Requires expertise to define bounds and hyperparameters for optimization.
Camp, C. V., & Bichon, B. J. (2004)	The SCE algorithm was applied to structural optimization, specifically the design of space trusses. The goal was to minimize the weight of the truss while ensuring stability and structural integrity.	numParams =4 numComplexes = 3 beta = 0,8 , alpha = 1,1	The SCE algorithm successfully reduced the weight of space trusses by up to 15% compared to other optimization methods, while maintaining safety	Effective in handling constraints in structural optimization problems. Robust in finding near-global optima for non-linear, multi-	Computationally expensive for large-scale structural problems. Requires careful tuning of algorithmic parameters to avoid premature

			and stability constraints.	modal design spaces.	convergence.
Grant ECE-86-10584, and by the National Weather Service, Grant NA85AA-H-HY088	The SCE method is a global optimization strategy designed to address challenges in solving high-dimensional, non-smooth, and non-convex optimization problems. It synthesizes several key concepts for effective and efficient global optimization	numParams =4 numComplexes = 2 beta = 1, alpha = 5	The SCE method consistently shows low failure rates and efficient evaluations compared to CRS2 and MSX. It handles complex optimization problems with multiple local minima effectively.	Adaptable to various objective function characteristics. Can address problems with discontinuous, non-smooth, and highly interactive parameters.	Requires parameter tuning for optimal performance. Computational demands increase for higher dimensional problems.

II-11 Related Work and Comparisons

Empirical choke correlations in the past have been derived from simple regression techniques or trial and error tuning. These conventional methods do not thoroughly search the parameter space. There is currently a trend towards the application of optimization algorithms; e.g., Mokhtari et al. (2021) optimized a choke-flow model for a retrograde gas-condensate field using a firefly algorithm. Likewise, genetic algorithms and particle swarm optimization are applied in well test analysis and reservoir calibration. In relation to these, SCE-UA has a unique set of strategies. Positively, SCE has been used as a benchmark in the literature for hydrologic and reservoir model calibration. Duan et al. (1994) demonstrated that it performed better than multistart simplex and other techniques for the case of watershed models. Muttil and Jayawardena (2008) modified SCE further and evaluated its reliability using standard test problems. Other evolutionary techniques, such as Differential Evolution (DE) or Genetic Algorithms (GA), share similar characteristics; however, SCE shuffling mechanism tends to facilitate quicker convergence for complex problems. For instance, Vrugt et al. (2003) generalized SCE for uncertainty quantification (SCEM), thereby illustrating its flexibility. Classical reservoir engineering methods, such as analytical well-test interpretation equations, depend on a series of simplifying assumptions. SCE calibration, by contrast, can accommodate more mechanistic choke models with greater detail or use neural-network predictors. It can also handle multi-objective problems, such as simultaneous fitting of gas and condensate production rates, by generalizing to multi-objective SCE variants (MOSCEM), but this is beyond the focus of the present discussion. In conclusion, there are limited methods specially developed for choke flow prediction documented in the literature. The novelty in the application of SCE is that it systematically searches the empirical model parameter space, perhaps yielding more generalizable and accurate correlations. Because field data are noisy and scarce, global robust search is preferable to local calibration.[31]

II-12 Conclusion:

The Shuffled Complex Evolution (SCE) algorithm is an efficient global optimization technique that was initially conceived for the calibration of hydrologic models. Its hybrid evolutionary approach coupling random sampling, simplex-directed local search, and occasional shuffling of subpopulations renders it particularly adept at addressing nonlinear, multi-dimensional issues. In reservoir engineering, the prediction of gas flow rates from condensate wells in chokes is merely one specific issue that can benefit from the strengths of SCE. The two-stage physics and empirical complexity of choke models lead to a formidable optimization problem, which can be addressed effectively by SCE via the extensive search of the parameter space. In contrast with conventional correlation fitting, SCE offers a systematic and automated calibration approach that has reduced sensitivity to starting assumptions. Relative to other optimization heuristics, SCE's population structure and intricate evolution tend to produce faster convergence on challenging problems. However, SCE also demands more computations and finer adjustment of its parameters. For practical use, engineers must weigh its advantages against the expense required. Nevertheless, in most contemporary applications, computing resources are adequate to implement SCE for choke flow calibration, particularly when the model evaluation process is not very expensive. Key Takeaways: Shuffled Complex Evolution (SCE) is a self-adaptive global optimizer ideally suited for calibrating sophisticated reservoir models. It works successfully in multimodal, nonlinear search spaces with no gradients In gas-condensate well choke flow, SCE has the capability to fit numerous empirical parameters at the same time, using its clustering and shuffling operations to avoid local traps. Its use should be contemplated when classical techniques provide poor fits or when a robust automatic calibration is required.

Chapter III

II. Chapter III: discusses the evaluation and results of parameters

III-1 Introduction

Accurately estimating the parameters that govern gas flow through choke valves is a critical step in optimizing production in gas fields. This chapter focuses on the use of a powerful global optimization method the Shuffled Complex Evolution (SCE) algorithm for the identification and calibration of unknown parameters in gas flow rate models. The primary objective is to extract the optimal values of these parameters by minimizing the error between the observed and simulated flow rates, using field data from the MLE gas field.

The model employed for this purpose is based on the empirical formulation introduced by Leal et al. (2013), which describes the nonlinear relationship between upstream pressure, downstream pressure, and gas flow rate across a choke. This model involves several unknown parameters commonly denoted as **alpha (α)**, **beta (β)**, **q**, and **m**, which need to be calibrated through inverse modeling. These parameters have physical relevance related to flow behavior, valve characteristics, and fluid properties.

To ensure a robust and accurate estimation, the **Shuffled Complex Evolution (SCE)** algorithm was selected due to its excellent performance in handling nonlinear, multimodal optimization problems. SCE has previously demonstrated superiority over traditional methods such as Gradient Descent and Levenberg-Marquardt in terms of convergence rate and resilience to initial conditions. It effectively combines global search via population evolution with local refinement through simplex operations, making it particularly suitable for noisy or poorly behaved objective functions.[32]

The identification process involves minimizing a cost function typically the Root Mean Square Error (RMSE) between the predicted flow rates and actual measurements. The algorithm operates on a population of potential solutions, evolving them through competitive complex evolution, reflection, contraction, and expansion. The key control parameters governing the behavior of SCE include:

- **q**: Number of points used in each simplex,
- **m**: Number of offspring generated in each evolution cycle,

- **α (alpha)**: Number of iterations performed within each complex before shuffling,
- **β (beta)**: Number of evolution steps per offspring generation.

Proper tuning of these parameters is essential to strike a balance between exploration and exploitation, reduce computational cost, and avoid premature convergence.

In the current study, field data from the MLE gas field was used to validate the parameter estimation process. This data consists of wellhead pressure, downstream pressure, and gas flow rate measurements over multiple operational conditions. The results are compared with published outcomes using Differential Evolution (DE) (ACO) algorithms from earlier studies to evaluate the effectiveness of SCE.

The goal of this chapter is therefore twofold:

1. To demonstrate the applicability and efficiency of the SCE algorithm for nonlinear gas flow modeling using real-world field data, and
2. To determine the optimal parameter configuration for accurate and robust estimation within the Leal model framework.

Through rigorous testing and comparative analysis, this chapter aims to show case the SCE algorithm as a viable and effective tool for parameter estimation in complex gas production systems.[33]

III-2 Subject description

The Berkhne basin is one of the most prospective hydrocarbon basins in Algeria, however its estimated reserves are still considered low compared to the possible quantities of hydrocarbons generated from the reservoir.

III-3 Geographies situation

The MLE field (Menzel Ledjmet East) is located south-east of Hassi Messaoud, about 220 km away at block level 405b in the Barkine basin.[34]

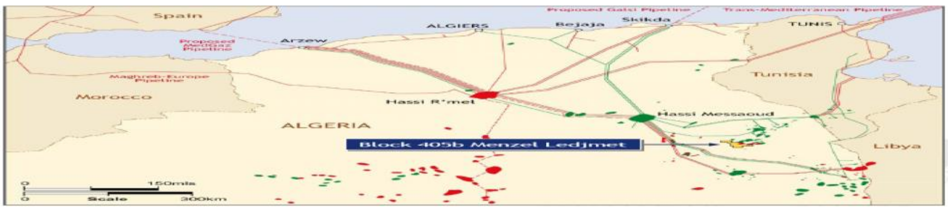

Figure (III.1): The geographical location of the MLE field (block 405)

III-4 Situation Geologies

This section is an overview of the main reservoir rocks in the MLE field.

The TAGI reservoir forms the basal sequence of the Mesozoic. Fluvial deposits that extend across the entire basin characterize it.

TAGI is divided into two main sequences:

- Lower TAGI, also known as the filling series, whose extent and thickness are governed by post-Hercynian pale topography.
- Middle to Upper TAGI, where anastomosing and sinuous channel formations dominate. The terminal sequences of the Upper TAGI in the central and northeastern parts of the Berkine Basin are marked by the onset of a marine transgressive phase at the base of the Triassic limestones.

III-4-1 Carboniferous reserves

From the Strunian to the Visean age, the Carboniferous reservoirs appear as sandstone intervals within clay and sandstone sequences, associated with a shallow marine depositional environment. The basal Carboniferous has a limited extent, confined to the central part and western edges of the Berkine Basin.

The proximal-type sandstone facies trend indicates the predominant influence of the ancient Amguid-Messaoud and Dahar uplifts, which served as the main source of sedimentary material. The Strunian–Carboniferous reservoirs have average thicknesses ranging from 20 to 50 meters and exhibit excellent petrophysical properties.

These sandstones produce condensate gas and oil at Menzel Lejmat, and oil at Rhourde El Khrouf (RKF).

III-4-2 Lower Devonian

The Lower Devonian reservoirs are represented by two major Gedinnian sequences, dominated by a series of massive fluvial sandstones (post-Caledonian) with an average thickness of approximately 200 meters, and the transgressive Siegenian, which includes reservoirs formed in interconnected sandstone beds corresponding to offshore bars and deltaic systems.

The facies distribution in the Lower Devonian is also strongly influenced by the Amguid-Messaoud structural high and the influx of clastic material into the southeastern Berkine Basin. These sandstones, which exhibit good petrophysical properties, are known to produce gas condensate and light oil in the MLSE and MLE areas.[35]

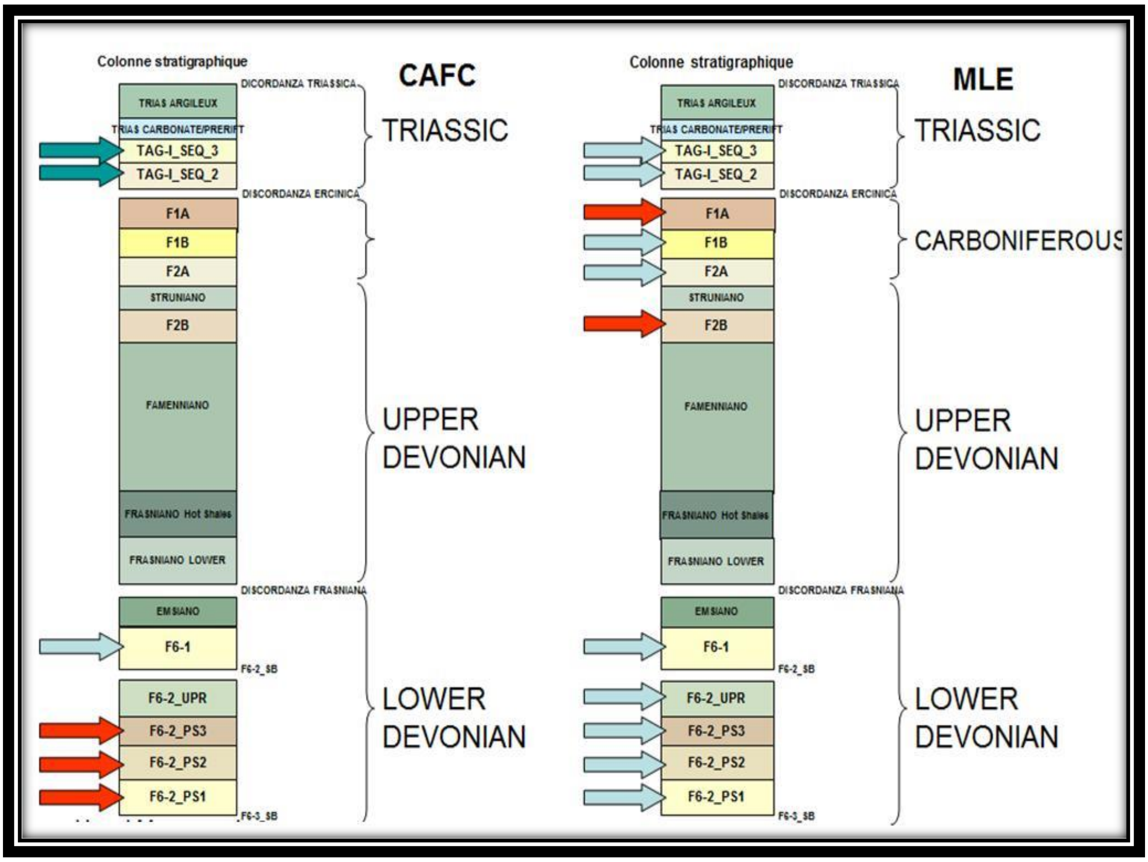

Figure (III.2): Block producing layers (405b)

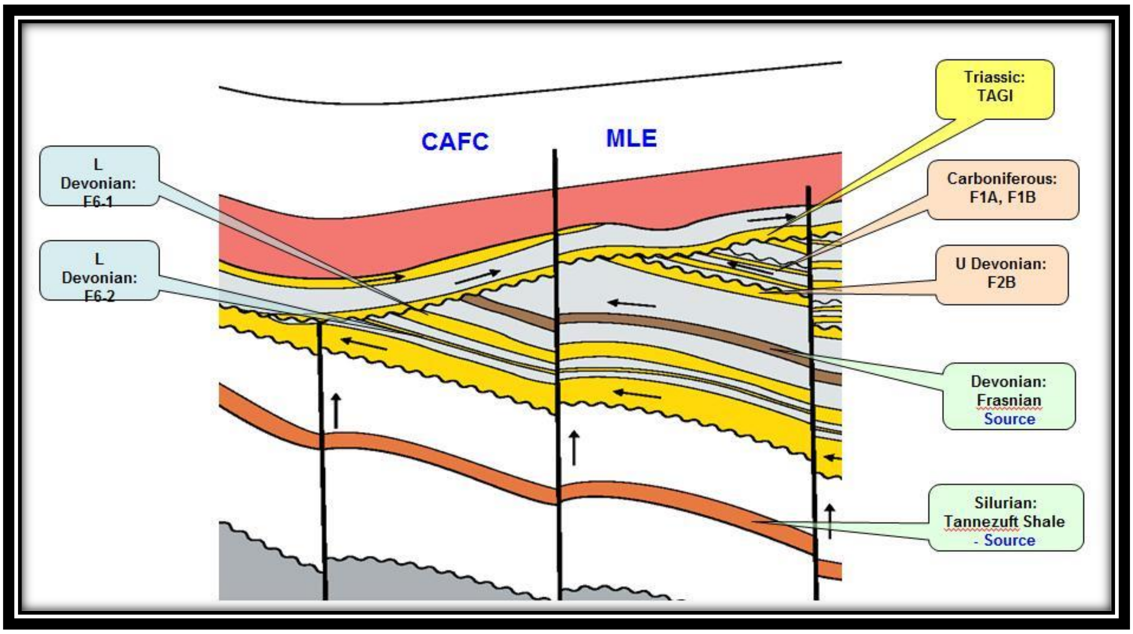

Figure (III.3): Block (405b) main tanks.

III-5 Descriptive Statistical summary of data sets

The database used in this study consists of 92 data points from wellhead choke tests related to the Pazanan 1 gas- condensate field in the Aghajari Region, South Iran. The second database used consist of 39 data points gathered from gas-condensate wells of MLE field the individual well test data is included is listed in the Table

Table (III.1): Statistical analysis for Fars province of Iran field dataset.

D64	y	pup	P down	T	GOR	Qg
1/64 inch		psig	psig	(F)	scf/STB	Mscf/day
Mean	0,72145	3199,5	1337,5	121,5	126442,5	27,93
Minimum	0,6229	284	80	80	2885	0,27
Maximum	0,82	6115	2595	163	250000	55,59

Table (III.2): Statistique analyses for MLE field dataset.

D64	y	pup	p down	T	GOR	Qg
1/64 inch		psig	psig	(F)	scf/STB	Mscf/day
Mean	48	1886,20266	598,8045061	124,5	27,36155655	0,768
Minimum	16	112	7	88	0,0631	0,666
Maximum	80	3660	1191	161	55	0,870

III-6 Shuffled Complex Evolution (SCE) Algorithm Configuration and Workflow

In this study, the selected optimization approach is the Shuffled Complex Evolution (SCE) algorithm, known for its robust global search capabilities and strong performance in solving nonlinear and multi-modal problems.

The SCE algorithm follows a structured sequence of steps designed to iteratively improve a population of candidate solutions toward an optimal set of parameters. The algorithm operates through the following key phases:

III-6-1 Initialization: The process begins by generating an initial population of candidate solutions randomly within the defined parameter space. Each solution is represented as a vector of real-valued parameters (e.g., α, β, q, m), corresponding to the model being calibrated. These individuals are evaluated using a predefined objective function (e.g., Root Mean Square Error).

III-6-2 Complex Formation: The population is sorted based on fitness values and partitioned into multiple subsets called complexes. Each complex is a mini-population that evolves independently, allowing parallel search paths within the overall population.[36]

III-6-3 Local Evolution (Simplex Search): Within each complex, the algorithm performs a series of local searches using a variant of the Nelder-Mead simplex method. Poor-performing solutions are perturbed by reflecting, contracting, or expanding the simplex around better solutions. This mechanism enables efficient exploration of local minima.

III-6-4 Shuffling and Recombination: After a defined number of iterations within each complex, the evolved individuals from all complexes are merged and shuffled. The updated population is then repartitioned into new complexes. This global recombination promotes information exchange across the entire search space and avoids premature convergence.

III-6-5 Selection and Replacement: Only individuals that yield better fitness values are retained in the population. Poor solutions are discarded, ensuring that each generation contains progressively improved candidates. This elitist strategy helps accelerate convergence toward the global optimum.

III-6-6 Termination Criteria: The algorithm proceeds through successive cycles of local evolution and shuffling until a stopping condition is satisfied. This can be based on reaching a maximum number of iterations, achieving a specified error threshold, or detecting stagnation in improvement.

Several key parameters, including the number of complexes (q), number of offspring (m), and local iteration steps per complex (α) govern the performance of the SCE algorithm. Proper tuning of these parameters is crucial to balance exploration (diversity across the global search space) and exploitation (intensive search within promising regions).

In this study, the SCE algorithm is applied to optimize the parameters of the Leal et al. (2013) gas flow model using real field data from the MLE gas reservoir. The resulting configuration was found to outperform conventional algorithms such as Differential Evolution (DE) and Genetic Algorithms (GA), particularly in terms of convergence speed, model accuracy, and robustness to noisy data.[37]

Evaluate the performance of the optimization algorithm, a series of experiments were conducted using the Shuffled Complex Evolution (SCE) algorithm. By analyzing the results, it becomes possible to determine the optimal configuration of algorithm parameters that yield the best model fitting and gas flow predictions.

The results are based on iterative testing using the SCE algorithm, where the number of iterations (loops) was set to 30. The objective is to minimize the discrepancy between the measured and calculated gas flow rates, thereby identifying the most accurate model parameters.

The objective function (OF), used to assess the quality of the optimization, is based on the Root Mean Square Error (RMSE). The equation is given as follows:

$$OF = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left(Q_{ig,est} - Q_{ig,exp}\right)^2} \qquad \text{(Eq.III.1)}$$

Where:

- **Qig.est** : the measured gas flow rate from wellhead test data,
- **Qig.exp** : the predicted (calculated) gas flow rate from the model,
- **N**: the number of data samples.

This function quantifies the average error between observed and modeled values, ensuring that the SCE algorithm focuses on minimizing this discrepancy during parameter optimization.[38]

Table (III.3): SCE parameter setting selection results

Case	Parameters			NFE	Time (sec)	MR	STD_g	RMSE_g
1	**LOOP 30**	numParams =6 numComplexes = 5 beta = 4 alpha =4	30	**8353**	**Best_time = 1,53**	**Worst V = 2.7767** **Best_V = 2,7767** **MAE =3 .1538e-06** **Mean_v = 2,7767**	4.3290e-06	5.2974e-06
			50	**6991**	**Best_time = 1,4**	**Worst_V = 2.7767** **Best_V = 2,7767** **MAE = 1.7144e-06** **Mean_v = 2,7767**	1.6730e-06	2.3759e-06
			70	**8583**	**Best_time =1,8**	**S_Worst_V = 2.7767** **S_Best_V = 2,7767** **MAE = 2.7073e-06** **Mean_v = 2,7767**	2.0575e-06	3.3796e-06
Grant ECE-		numParams =4 numComplexes =	30	**7316**	**Best_time = 1,74**	**Worst_V = 2.7767** **Best_V = 2,7767**	4.2257e-06	5.1991e-06

86-1058		5 beta =1 alpha =5				**MAE = 3.1255e-06** **Mean_v = 2,7767**		
			50	**5233**	**Best_time = 1,72**	**Worst_V = 2.7767** **Best_V = 2,7767** **MAE = 7.2130e-06** **Mean_v = 2,7767**	7.9509e-06	1.0637e-05
			70	**6740**	**Best_time =1,87**	**Worst_V = 2.7767** **Best_V = 2,7767** **MAE = 3.7651e-06** **Mean_v = 2,7767**	2.7083e-06	4.6115e-06
Author Single diode dim-5		numParams =2 numComplexes =7 beta = 6 alpha =6	30	**6,28E+03**	**Best_time = 1,10**	**Worst_V = 2.7767** **Best_V = 2,7767** **MAE = 2.3228e-05** **Mean_v = 2,7767**	3.9720e-05	4.5438e-05
			50	**6740**	**Best_time = 1,17**	**Worst_V = 2.7767** **Best_V = 2,7767** **MAE = 4.1622e-05** **Mean_v = 2,7767**	4.3448e-05	5.9642e-05
			70	**1,07E+04**	**Best_time = 1,77**	**Worst_V = 2.7767** **Best_V = 2,7767** **MAE = 1.8697e-05** **Mean_v = 2,7767**	3.6904e-05	4.0817e-05
Camp, C. V., & Bichon, B. J. (2004)		numParams =4 numComplexes = 3 beta = 0,8 alpha =1,1	30	**4205**	**Best_time = 1,53**	**Worst_V = 2.7767** **Best_V = 2,7767** **MAE = 0.0021** **Mean_v = 2,7767**	0.0108	0.0108
			50	**5327**	**Best_time = 2,5**	**Worst_V = 2.8359** **Best_V = 2,7767** **MAE = 7.9044e-07** **Mean_v = 2,7767**	4.4032e-07	9.0123e-07
			70	**1,14E+04**	**Best_time = 3,97**	**Worst_V = 2.7767** **Best_V = 2,7767** **MAE = 1.9101e-06** **Mean_v = 2,7767**	1.2672e-06	2.2805e-06

Table (III.4): The best results according to the previous tests are presented in Table

Case	Parameters			NFE	Time (sec)	MR	STD_g	RMSE_g
SCE	30	numParams =4 numComplexes = 3 beta = 0,8 alpha =1,1	50	5327	Best_time = 2,5	Worst_V = 2.8359	4.4032e-07	9.0123e-07
						Best_V = 2,7767		
						MAE = 7.9044e-07		
						Mean_v = 2,7767		

III-7 Results Description and Discussion

The performance of the **Shuffled Complex Evolution (SCE) algorithm** was evaluated and compared against two benchmark optimization methods: **Differential Evolution (DE)** and **Ant Colony Optimization (ACO)**. The comparison focused on the ability of each algorithm to accurately estimate the parameters of the gas flow rate model based on real wellhead data.

All experiments were performed using a personal computer equipped with an **Intel® Core™ i5-7200U CPU @ 2.50 GHz (up to 2.70 GHz)** and **8.00 GB of RAM**, running in a **MATLAB 2013** environment. This ensures a fair and practical benchmark of the algorithm's performance on standard engineering computing resources.

The evaluation relied on four key statistical metrics:

- Root Mean Square Error (RMSE)**,**
- Mean Absolute Error (MAE)**,**
- Coefficient of Détermination (R^2)**,**
- Correlation Coefficient (R)**.**

These indicators provide both an error-based and a correlation-based assessment of model accuracy and reliability.

Among all tested configurations**,** only the result with the lowest standard deviation (STD = 4.4032e-07) was selected for analysis, as it reflects the most stable and repeatable outcome.

The findings show that the SCE algorithm outperformed both DE and ACO in terms of solution accuracy, convergence speed, and robustness to parameter sensitivity.

Specifically:

- SCE achieved the lowest RMSE and MAE values, confirming its effectiveness in minimizing prediction error.
- It also delivered higher R^2 and correlation values, indicating a better match between the model's predictions and actual field measurements.
- Furthermore, SCE required fewer iterations to reach optimal or near-optimal solutions, demonstrating its efficiency and convergence reliability.

These results confirm that, under the same computational conditions, SCE is a superior choice for solving parameter estimation problems in nonlinear gas flow modeling. Its ability to deliver stable results with low variance (as evidenced by the selected low STD case) further reinforces its suitability for real-world petroleum engineering applications.[39]

$$MAE = \frac{1}{N}\sum_{i=1}^{N} abs(OF - OF_{best}) \quad \text{(Eq.III.2)}$$

$$STD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(OF - OF_{mean})^2} \quad \text{(Eq.III.3)}$$

$$RE = \frac{1}{OF_{best}}\sum_{i=1}^{N}(OF - OF_{best}) \quad \text{(Eq.III.4)}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(OF - OF_{best})^2} \quad \text{(Eq.III.5)}$$

III-8 Performance Comparison and Interpretation:

The results of the performance comparison are summarized below, where the parameter settings of the Shuffled Complex Evolution (SCE) algorithm were configured as follows: **α = 1.1**, **β = 0.8**, **q = 4**, **m = 3**, with a population size of 50, loop count of 30, and a total of 50,000 function evaluations (NFE). These settings were selected to ensure a balanced trade-off between exploration and exploitation across the search space.

The same problem was also tested using the Differential Evolution (DE) and Ant Colony Optimization (ACO) algorithms. For fairness and consistency, the DE parameters were fixed across all tests: **Crossover Probability (Cr) = 0.75**, **Scaling Factor (F) = 0.5**, and a **maximum number of iterations = 30**.

The comparison was made primarily based on the Standard Deviation (STD) of the solutions obtained across multiple independent runs, reflecting the stability and robustness of each algorithm. The results are shown in the following summary

Table (III.5): Performance test using a maximum NFE of 50000 (NP = 50 & N_it = 30)

Case	Parameters			NFE	Time (sec)	MR	STD_g	RMSE_g
ACO	30	q=0,5 zeta=0,5	50	**4,81E+04**	**Best_time = 8,3**	**Worst_V = 7.3235**	1.4587	2.2540
						Best_V = 2.9891		
						MAE = 1.9367		
						Mean_v = 4.9258		
DE	30	beta_min=0.69 beta_max=0.7 pCR=0.75	50	**1,93E+04**	**Best_time = 3,29**	**Worst_V = 3.1054**	0.1610	0.1990
						Best_V = 2,7767		
						MAE = 0.1207		
						Mean_v = 2.7836		
SCE	30	numParams =4 numComplexes = 3 beta = 0,8 alpha =1,1	50	**5327**	**Best_time = 2,5**	**Worst_V = 2.8359**	4.4032e-07	9.0123e-07
						Best_V = 2,7767		
						MAE = 7.9044e-07		
						Mean_v = 2,7767		

Table presents the performance comparison of the SCE, DE, and ACO algorithms using a maximum NFE of 50,000 (population size = 50, loop = 30). From this table, it can be observed that the RMSE value achieved by the SCE algorithm is 9.0123e-07, which is significantly lower than that obtained by DE (0.1990) and ACO (2.2540). Furthermore, SCE also yielded the lowest standard deviation (STD = 4.4032e-07), indicating the highest stability and robustness across runs, compared to DE (STD = 0.1610) and ACO (STD=1.4587). In terms of computational time, SCE executed in approximately 2.5 seconds, which is faster than DE (3.29 s) and significantly faster than ACO (8.3 s). These results demonstrate that SCE not only provides the most accurate and consistent results but also offers superior computational efficiency, making it more suitable for both offline and real-time applications.

Table (III.6): Optimal β_1 to β_5 constants ,derived in this study using the SCE algorithm with a population size of 50 and 50,000 function evaluations (NFE), are presented and compared with those proposed by Leal et al. (2013).

stastatique paramètre	MAE	RMSE	R^2
this stady	7.9044e-07	9.0123e-07	0.9566
DE	0.1317	0.2079	0,9564
ACO	2.2675	2.5729	0.8647
Leal	2,55E-06	3,62E-06	0,9439
Hamzeh Ghorbani,	2,10E-06	2,90E-06	0.9566

Table (III.7): Statistical performance measures comparing the optimal β_1 to β_5 constants derived in this study using the SCE algorithm with those proposed by Leal et al. (2013), as well as results obtained using DE and ACO algorithms.

Optimum β value	β1	β2	β3	β4	β5
this stady	0,079147153	2,108306732	0,108641592	1,426920566	1,431842325
Leal	0.00149228	2.118654173	1.586085251	0.739034	1.369516866
Hamzeh Ghorbani,	0,1	2,3481935	0,0001	1,0360972	1,498291

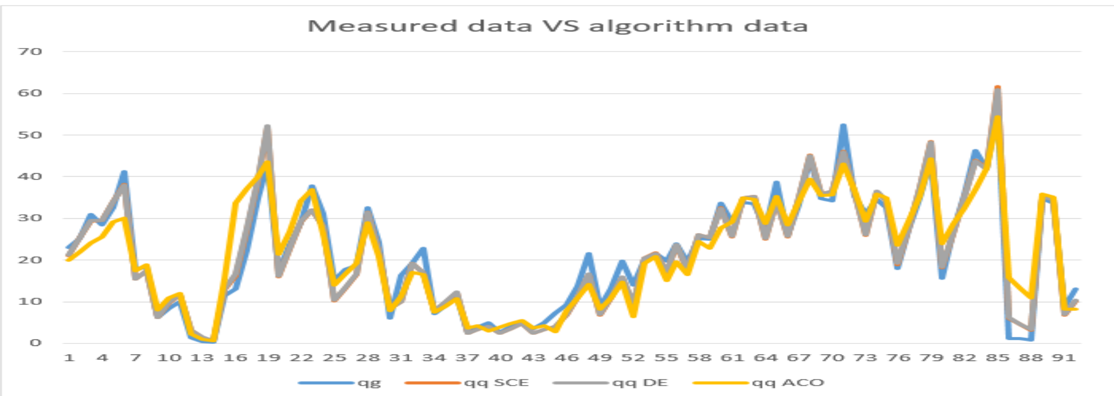

Figure (III.3): Measured and calculated gas flow rates presentation using SCE and

DE and ACO algorithms.

In order to verify and assess the performance of the Shuffled Complex Evolution (SCE) algorithm in comparison to Differential Evolution (DE) and Ant Colony Optimization (ACO) algorithms, the Absolute Error of the estimated gas flow rates has been computed and summarized in Table

Table (III.8): the Absolute Error of the estimated gas flow rates

qg	qq SCE	qq DE	qq ACO	Absolute Error Qg (SCE)	Absolute Error Qg (DE)	Absolute Error Qg (ACO)
23,07	21,075447	21,20806	19,916589	1,994553424	1,861940798	3,153411151
25,19	25,281589	25,3778	21,992546	0,091588734	0,187804531	3,197454328
30,9	29,403279	29,44652	24,169751	1,496721098	1,453481803	6,730249269
28,431	29,456987	29,49763	25,560469	1,025987084	1,066626763	2,870531171
32,498	34,119218	34,0908	29,19117	1,621217773	1,592798348	3,306829781
41,28	38,159108	38,05195	30,01137	3,120892058	3,228046677	11,26863016
17,56	15,388508	15,48184	17,464167	2,171492201	2,078162725	0,095833372
18,44	17,408639	17,47039	18,927325	1,031360782	0,969607284	0,487324818
6,24	6,1871077	6,305814	8,0559102	0,052892283	0,065814411	1,815910157
8,369	9,7233173	9,840239	10,838044	1,354317325	1,471239355	2,469043507
9,986	11,553256	11,65725	11,955033	1,56725645	1,67125432	1,969032843
1,307	3,1677797	3,236584	2,3264223	1,8607797	1,92958386	1,019422275
0,52	1,400045	1,446104	1,0307425	0,880045037	0,926103618	0,510742524
0,27	0,5854405	0,61236	0,6292295	0,315440534	0,342359615	0,359229456
11,38	12,972283	13,12693	15,358094	1,592283097	1,746928193	3,978094001
13,12	16,223981	16,67877	33,640919	3,103981171	3,558765278	20,52091896
22,26	27,034817	27,5506	37,013858	4,774817262	5,290604026	14,7538577
34,72	38,829547	39,30351	39,907502	4,109546599	4,583512794	5,1875023
43,25	51,876906	52,21776	43,523357	8,626906497	8,967756145	0,273356668
17,25	16,011944	16,20082	21,3018	1,238056183	1,049183505	4,051799828
23,76	22,736236	22,87376	26,737506	1,023764264	0,886235516	2,977505634
29	29,231892	29,26865	34,174095	0,231892105	0,268647179	5,174094947
37,85	32,118157	32,02869	36,876586	5,731842617	5,821311502	0,973413935
31,1	28,088617	28,12478	26,303349	3,011383462	2,975222645	4,796651342

15,145	10,269215	10,46512	14,075423	4,875784997	4,679884949	1,069577387
17,729	13,189609	13,39134	16,68981	4,539391456	4,337661413	1,039189549
18,659	16,554754	16,75267	19,181669	2,104245803	1,906330128	0,522668717
32,6	31,468261	31,50931	28,964313	1,13173892	1,090685731	3,635687017
24,21	22,093928	22,12227	20,788535	2,116071924	2,087725286	3,421464952
6,125	8,3077459	8,441577	7,8549672	2,182745895	2,316576857	1,729967154
16,246	9,9784201	10,09804	11,346964	6,267579942	6,147962745	4,899035931
19,261	19,213949	19,23992	17,003915	0,047051268	0,02107819	2,25708489
22,824	16,81052	16,83156	16,491703	6,013480068	5,992438892	6,332297113
7,109	7,5787967	7,767601	7,5420895	0,469796661	0,658600691	0,433089456
9,192	9,8274532	10,02843	9,0144413	0,635453207	0,836429864	0,177558709
11,301	12,124557	12,32352	10,657892	0,823557047	1,02252035	0,643107624
2,42	2,3455818	2,373217	3,6400471	0,074418187	0,046782623	1,220047097
3,8	3,288625	3,308532	4,2773653	0,511375016	0,491467833	0,477365333
4,89	4,0206652	4,027295	3,0442935	0,869334758	0,862704674	1,845706466
2,67	2,4391968	2,467946	3,8192144	0,230803194	0,202053695	1,149214389
3,97	3,49524	3,516487	4,7544721	0,474760007	0,453512512	0,78447205
5,29	4,6948022	4,700732	5,5342879	0,595197788	0,589267642	0,244287933
3,58	2,3881605	2,416274	3,6076467	1,191839474	1,163726289	0,027646661
4,9	3,3930521	3,413557	4,2529764	1,506947912	1,486443163	0,647023642
7,25	3,9949347	4,00208	2,8700012	3,255065267	3,247919954	4,379998808
9,375	6,7677132	6,899661	7,8677373	2,607286849	2,475338556	1,507262682
13,786	11,157587	11,29538	10,877472	2,628413255	2,490615397	2,90852837
21,605	16,53089	16,63861	14,151539	5,074109902	4,966394415	7,453460927
8,78	6,8436722	6,976646	8,1301168	1,936327805	1,803354308	0,649883156
13,23	10,886682	11,02029	10,910591	2,343318204	2,209712544	2,319409282
19,83	15,800681	15,90046	14,760373	4,029318917	3,929541213	5,069626863
14,04	9,3047082	9,433146	6,4077656	4,735291843	4,606853544	7,63223444
20,178	20,426549	20,45281	19,162634	0,248548523	0,27481126	1,015366268
21,66	21,694667	21,63123	20,904886	0,034666861	0,028765875	0,755113933
19,836	17,083463	17,19353	15,056799	2,75253718	2,642472939	4,779201389
23,959	23,618339	23,65277	19,546456	0,34066141	0,306225378	4,412543963
19,558	17,666093	17,77774	16,460505	1,891907059	1,780258755	3,097495021
25,137	26,130288	26,1639	24,498726	0,993288328	1,02689897	0,638274026
25,02	25,313763	25,34727	22,906048	0,293762734	0,327270268	2,113952383
33,642	32,577044	32,48299	27,679912	1,064955578	1,159008171	5,962088146
29,12	25,595777	25,75099	29,088999	3,524222506	3,36900774	0,031000615
33,83	34,97238	35,01585	34,866904	1,14237991	1,185848095	1,036904071
33,43	35,303972	35,34815	34,652039	1,873972239	1,918150322	1,222039106
27,278	25,08048	25,23242	28,821942	2,197520317	2,045577615	1,543941652

38,667	34,197273	34,23935	35,298849	4,469727102	4,427647968	3,368151127
25,982	25,611399	25,76708	28,467579	0,37060066	0,214922087	2,485578977
33,274	34,921471	34,96533	34,031032	1,647470646	1,691326322	0,757031901
44,559	45,226076	45,09478	39,377786	0,667075668	0,535778789	5,181213812
34,767	35,751564	35,79608	35,476097	0,984563819	1,029084862	0,709097081
34,18	36,473448	36,51913	35,730548	2,293448172	2,339132375	1,550547669
52,38	46,045955	45,91125	43,00074	6,334045173	6,468745869	9,379260467
35,33	36,212139	36,25688	36,760423	0,882139467	0,926875016	1,430423218
31,07	25,98777	26,14542	29,412563	5,08222975	4,924575176	1,657436958
34,56	36,436349	36,48194	35,773433	1,876348517	1,921937593	1,213432795
32,53	34,151797	34,19392	34,866173	1,62179734	1,663923056	2,336173442
17,93	18,936407	19,16086	23,613547	1,006406598	1,23086205	5,683546719
27,44	27,505487	27,67363	29,382367	0,065487415	0,233633331	1,942367111
35,02	37,304672	37,35233	35,317718	2,284672462	2,332332368	0,297717962
44,14	48,399726	48,25825	44,396853	4,259725552	4,118251937	0,256853004
15,65	18,157673	18,37199	23,892634	2,507673275	2,721994121	8,242634365
26,83	26,272928	26,43304	28,639626	0,55707167	0,396962632	1,809626195
35,68	35,029478	35,07492	32,469931	0,65052236	0,605078338	3,210068943
46,23	43,910123	43,78368	36,948799	2,319876902	2,44631674	9,281201163
41,94	41,913747	41,79167	41,964725	0,026253487	0,148327768	0,024724613
55,59	61,589745	60,98899	54,450196	5,99974501	5,398986343	1,139804224
1,204	6,0288623	6,145464	15,715637	4,824862307	4,941463795	14,51163744
1,111	4,5483755	4,655589	13,345693	3,437375539	3,544589309	12,23469309
0,753	3,2003284	3,291527	10,83578	2,447328387	2,538527227	10,08278007
34,73	35,030076	35,07325	35,880504	0,30007594	0,343250391	1,150504307
33,724	34,607705	34,65049	35,040427	0,883704836	0,926490976	1,316427244
8,78	6,8436722	6,976646	8,1301168	1,936327805	1,803354308	0,649883156
13,106	10,181311	10,31414	8,1878822	2,924688817	2,791860748	4,918117842
				194,3193906	**194,8471012**	**299,8465922**

Table (III.9) : Data sets présentation

Well	**D**	**pup**	**p down**	**T**	**Qg**	**G**
Name	1/64	PSI	PSI	F	Mscf/day	G
1	48	779	691	117	0,600350	0,74000000
2	52	936	689	119	0,335490	0,73900000

3	56	838	689	152	0,586224	0,74000000
4	56	1025	713	158	4,128606	0,75500000
5	60	1163	638	161	1,695106	0,74800000
6	64	838	794	106	0,164849	0,66600000
7	48	794	779	107	0,252500	0,66600000
8	52	1411	926	108	1,200700	0,71680000
9	32	1544	941	88	0,942902	0,71200000
10	40	1544	941	89	0,945834	0,71680000
11	44	1411	926	92	1,894987	0,71680000
12	32	1352	838	106	0,860125	0,70100000
13	24	1264	823	108	1,266103	0,70100000
14	16	1455	823	110	0,510242	0,71800000
15	40	485	206	144	2,698457	0,87000000
16	24	2029	1117	116	9,282342	0,72200000
17	32	2234	1117	117	2,248684	0,71100000
18	40	1896	1147	120	1,503998	0,71900000
19	48	2587	1191	120	3,375360	0,69600000
20	40	2484	1191	117	3,743358	0,70000000
21	48	2367	1191	116	4,237764	0,70400000
22	56	1985	1191	109	3,248952	0,71100000
23	64	2132	1161	104	2,366085	0,70500000
24	56	897	662	118	2,059341	0,71300000
25	32	897	697	118	2,680633	0,71400000
26	38	676	647	124	0,496172	0,72000000
27	40	1441	1029	125	5,049296	0,74300000
28	56	1352	1044	128	7,006366	0,75300000
29	56	1338	1029	128	7,116866	0,75300000
30	36	1470	1000	136	3,620463	0,74500000
31	40	1250	1014	138	3,699568	0,74300000
32	56	1220	1029	126	4,030467	0,74000000
33	56	2440	794	132	6,402696	0,71500000

34	28	2367	794	135	8,058073	0,72300000
35	32	2499	779	134	3,805547	0,71600000
36	36	3646	1173	135	6,675185	0,70000000
37	40	3543	1173	134	9,245035	0,70200000
38	48	2117	1164	125	23,942660	0,70500000
39	56	2595	967	108	3,065411	0,70600000
40	40	3660	970	130	20,021740	0,71400000
41	48	3593	1011	129	24,115184	0,71400000
42	56	932	914	128	5,773953	0,78900000
43	40	1036	898	113	2,518644	0,75400000
44	48	490	451	136	4,907684	0,78400000
45	56	573	456	110	3,178323	0,76400000
46	32	515	456	111	0,529721	0,74200000
47	40	529	475	112	54,660000	0,78200000
48	48	569	470	118	21,640000	0,77200000
49	32	484	472	117	13,880000	0,77600000
50	40	441	441	122	0,801291	0,76600000
51	48	962	769	126	2,986423	0,77600000
52	40	959	806	131	3,115993	0,71300000
53	56	952	766	135	3,163844	0,72100000
54	64	969	929	136	0,383164	0,71000000
55	48	1213	864	120	0,943256	0,72500000
56	56	1610	647	115	0,857794	0,72300000
57	48	1576	669	110	1,259675	0,72200000
58	56	941	353	120	2,445868	0,82800000
59	56	2078	824	133	5,921226	0,71926531
60	48	334	7	120	0,074926	0,73000000
61	56	348	15	109	0,063113	0,73000000
62	56	340	7	110	0,065000	0,73000000
63	56	183	71	144	0,072766	0,73000000
64	48	1520	838	116	2,136216	0,72444898

65	56	1547	918	117	3,403870	0,72689796
66	48	2535	802	120	0,299961	0,70400830
67	56	2583	758	120	1,967641	0,70555102
68	64	2348	734	117	2,828956	0,71779592
69	56	391	173	116	0,792815	0,83600000
70	56	350	172	109	0,584811	0,83600000
71	64	307	153	104	0,508171	0,83400000
72	56	3020	778	118	5,138289	0,69400000
73	48	298	272	118	1,503311	0,78300000
74	56	508	193	124	0,822974	0,83800000
75	56	242	178	125	0,674052	0,77400000
76	40	1430	919	128	4,144498	0,74300000
77	48	139	97	128	2,910744	0,76700000
78	56	221	116	136	2,825449	0,74853061
79	64	151	122	138	1,729774	0,72448980
80	40	208	95	126	1,535476	0,74053061
81	48	408	129	132	3,864281	0,84053061
82	56	393	219	135	0,703576	0,70951020
83	64	112	109	134	1,290667	0,74946939
84	64	1212	853	135	1,634536	0,72142857
85	80	3425	1017	134	5,226088	0,69302041
86	32	3337	1016	125	5,887169	0,68465306
87	28	3175	1083	108	6,960339	0,69265306
88	24	3043	1005	130	5,057752	0,68265306
89	66	2896	1020	129	6,415842	0,68734694
90	56	3146	1034	128	28,080339	0,68500000
91	32	2092	781	113	3,568251	0,69700000
92	40	1398	939	117	2,873937	0,73100000
93	38	1174	855	119	1,645153	0,73100000
94	50	1391	819	152	1,430929	0,70300000
95	34	1185	793	158	0,692791	0,70300000

96	30	670	657	161	0,343789	0,71900000
97	8	1442	664	106	1,835968	0,68500000
98	12	2695	658	107	4,528417	0,68000000
99	34	1434	656	108	2,623027	0,67500000
100	16	1239	662	88	9,217868	0,70600000
101	34	720	587	89	2,720321	0,71800000
102	38	838	588	92	4,919702	0,72500000
103	50	265	102	106	3,626644	0,83191837
104	34	94	77	108	0,135898	0,79265306
105	26	265	39	120	0,627739	0,77170833
106	28	190	52	112	0,616195	0,75420833
107	32	166	22	92	0,644617	0,75098630
108	36	121	59	102	0,664390	0,77180822

III-9 Conclusion

In this chapter, the problem of parameter identification for the gas flow rate model has been addressed using three well-established metaheuristic optimization algorithms: Ant Colony Optimization (ACO)**,** Differential Evolution (DE)**,** and Shuffled Complex Evolution (SCE). All algorithms were executed under identical experimental conditions: a fixed loop count of 30, a population size of 50, and a maximum of 50,000 function evaluations (NFE)**.**

The comparative results clearly highlight distinct performance behaviors among the algorithms. While ACO achieved moderate accuracy, it was the most time-consuming and demonstrated high variability in its outcomes, as reflected in its large standard deviation (STD). DE, on the other hand, showed improved performance and greater consistency than ACO, achieving lower RMSE and reduced computational time.

However, the SCE algorithm outperformed both ACO and DE across all key performance indicators. It achieved the lowest RMSE (9.0123e-07)**,** the smallest standard deviation (4.4032e-07), and shorter runtime (2.5 s). These results clearly demonstrate that SCE provides the most accurate, stable, and computationally efficient solution for the gas flow rate-modeling task.

In conclusion, under the constraints of this study, the Shuffled Complex Evolution (SCE) algorithm proves to be the most powerful and reliable optimization technique. Its balance between global search capability and local refinement, combined with its robustness to parameter sensitivity, makes it the most suitable choice for real-world applications in petroleum engineering, especially when precision and stability are critical.

1. General Conclusion

In conclusion, the gas flow rates from gas-condensate reservoirs through wellhead chokes have been successfully predicted in this study using advanced metaheuristic optimization algorithms. The focus was placed on extracting accurate model parameters for the gas flow rate model developed by Leal et al. (2013), which was selected based on its suitability and compatibility with the available field data.

Two comprehensive datasets were used to validate the model: 92 datasets from several wells in Iran and 108 datasets from the MLE gas field. These datasets provided a broad and reliable basis for evaluating the model's predictive performance across different reservoir conditions.Three optimization algorithms were explored in this study:

- Ant Colony Optimization (ACO)
- Differential Evolution (DE)
- Shuffled Complex Evolution (SCE)

All algorithms were configured under identical conditions: a population size of 50, loop count of 30, and a maximum of 50,000 function evaluations (NFE). The SCE algorithm parameters were tuned based on the control variables alpha, beta, gamma, m, and q, selected through preliminary testing to ensure a balance between convergence speed and solution accuracy.

Among the tested algorithms, SCE emerged as the most effective and stable, achieving the lowest Root Mean Square Error (RMSE = 9.0123e-07) and the smallest Standard Deviation (STD = 4.4032e-07), while also demonstrating superior computational efficiency (execution time = 2.5 seconds). In contrast, DE achieved moderate accuracy and stability, while ACO showed high variability and longer run times, making it less suitable for real-time applications.

These results highlight the critical role of algorithm selection and parameter configuration in solving nonlinear inverse modeling problems in reservoir engineering. The superior performance of SCE underlines its capability to accurately calibrate the Leal model using diverse field data, and its robustness makes it a strong candidate for broader industrial applications where stability and precision are paramount.

Overall, the findings of this study confirm that the SCE algorithm provides the best trade-off between accuracy, robustness, and computational efficiency in gas flow rate modeling tasks, successfully estimating key model parameters and outperforming other tested optimization strategies.

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Annexe

Table (III.9) : Data sets présentation

Well	**D**	**pup**	**p down**	**T**	**Qg**	**G**
Name	1/64	PSI	PSI	F	Mscf/day	G
1	48	779	691	117	0,600350	0,74000000
2	52	936	689	119	0,335490	0,73900000
3	56	838	689	152	0,586224	0,74000000
4	56	1025	713	158	4,128606	0,75500000
5	60	1163	638	161	1,695106	0,74800000
6	64	838	794	106	0,164849	0,66600000
7	48	794	779	107	0,252500	0,66600000
8	52	1411	926	108	1,200700	0,71680000
9	32	1544	941	88	0,942902	0,71200000
10	40	1544	941	89	0,945834	0,71680000
11	44	1411	926	92	1,894987	0,71680000
12	32	1352	838	106	0,860125	0,70100000
13	24	1264	823	108	1,266103	0,70100000
14	16	1455	823	110	0,510242	0,71800000
15	40	485	206	144	2,698457	0,87000000
16	24	2029	1117	116	9,282342	0,72200000
17	32	2234	1117	117	2,248684	0,71100000
18	40	1896	1147	120	1,503998	0,71900000
19	48	2587	1191	120	3,375360	0,69600000
20	40	2484	1191	117	3,743358	0,70000000
21	48	2367	1191	116	4,237764	0,70400000
22	56	1985	1191	109	3,248952	0,71100000
23	64	2132	1161	104	2,366085	0,70500000
24	56	897	662	118	2,059341	0,71300000
25	32	897	697	118	2,680633	0,71400000
26	38	676	647	124	0,496172	0,72000000
27	40	1441	1029	125	5,049296	0,74300000

28	56	1352	1044	128	7,006366	0,75300000
29	56	1338	1029	128	7,116866	0,75300000
30	36	1470	1000	136	3,620463	0,74500000
31	40	1250	1014	138	3,699568	0,74300000
32	56	1220	1029	126	4,030467	0,74000000
33	56	2440	794	132	6,402696	0,71500000
34	28	2367	794	135	8,058073	0,72300000
35	32	2499	779	134	3,805547	0,71600000
36	36	3646	1173	135	6,675185	0,70000000
37	40	3543	1173	134	9,245035	0,70200000
38	48	2117	1164	125	23,942660	0,70500000
39	56	2595	967	108	3,065411	0,70600000
40	40	3660	970	130	20,021740	0,71400000
41	48	3593	1011	129	24,115184	0,71400000
42	56	932	914	128	5,773953	0,78900000
43	40	1036	898	113	2,518644	0,75400000
44	48	490	451	136	4,907684	0,78400000
45	56	573	456	110	3,178323	0,76400000
46	32	515	456	111	0,529721	0,74200000
47	40	529	475	112	54,660000	0,78200000
48	48	569	470	118	21,640000	0,77200000
49	32	484	472	117	13,880000	0,77600000
50	40	441	441	122	0,801291	0,76600000
51	48	962	769	126	2,986423	0,77600000
52	40	959	806	131	3,115993	0,71300000
53	56	952	766	135	3,163844	0,72100000
54	64	969	929	136	0,383164	0,71000000
55	48	1213	864	120	0,943256	0,72500000
56	56	1610	647	115	0,857794	0,72300000
57	48	1576	669	110	1,259675	0,72200000
58	56	941	353	120	2,445868	0,82800000
59	56	2078	824	133	5,921226	0,71926531

60	48	334	7	120	0,074926	0,73000000
61	56	348	15	109	0,063113	0,73000000
62	56	340	7	110	0,065000	0,73000000
63	56	183	71	144	0,072766	0,73000000
64	48	1520	838	116	2,136216	0,72444898
65	56	1547	918	117	3,403870	0,72689796
66	48	2535	802	120	0,299961	0,70400830
67	56	2583	758	120	1,967641	0,70555102
68	64	2348	734	117	2,828956	0,71779592
69	56	391	173	116	0,792815	0,83600000
70	56	350	172	109	0,584811	0,83600000
71	64	307	153	104	0,508171	0,83400000
72	56	3020	778	118	5,138289	0,69400000
73	48	298	272	118	1,503311	0,78300000
74	56	508	193	124	0,822974	0,83800000
75	56	242	178	125	0,674052	0,77400000
76	40	1430	919	128	4,144498	0,74300000
77	48	139	97	128	2,910744	0,76700000
78	56	221	116	136	2,825449	0,74853061
79	64	151	122	138	1,729774	0,72448980
80	40	208	95	126	1,535476	0,74053061
81	48	408	129	132	3,864281	0,84053061
82	56	393	219	135	0,703576	0,70951020
83	64	112	109	134	1,290667	0,74946939
84	64	1212	853	135	1,634536	0,72142857
85	80	3425	1017	134	5,226088	0,69302041
86	32	3337	1016	125	5,887169	0,68465306
87	28	3175	1083	108	6,960339	0,69265306
88	24	3043	1005	130	5,057752	0,68265306
89	66	2896	1020	129	6,415842	0,68734694
90	56	3146	1034	128	28,080339	0,68500000
91	32	2092	781	113	3,568251	0,69700000

92	40	1398	939	117	2,873937	0,73100000
93	38	1174	855	119	1,645153	0,73100000
94	50	1391	819	152	1,430929	0,70300000
95	34	1185	793	158	0,692791	0,70300000
96	30	670	657	161	0,343789	0,71900000
97	8	1442	664	106	1,835968	0,68500000
98	12	2695	658	107	4,528417	0,68000000
99	34	1434	656	108	2,623027	0,67500000
100	16	1239	662	88	9,217868	0,70600000
101	34	720	587	89	2,720321	0,71800000
102	38	838	588	92	4,919702	0,72500000
103	50	265	102	106	3,626644	0,83191837
104	34	94	77	108	0,135898	0,79265306
105	26	265	39	120	0,627739	0,77170833
106	28	190	52	112	0,616195	0,75420833
107	32	166	22	92	0,644617	0,75098630
108	36	121	59	102	0,664390	0,77180822

92 wellhead-flow-test-data samples from the pazanan 1 gaz-condensate field (aghajari region, south iran)

welle number	sample number	choke diameter	gaz gravity	upside pressure	downside pressure	fluif flowing temperature °F	gaz condensate ration	gaz flow rate
well no	index	D64	y	pup	p down	T	GOR	Qg
		1/64 inch		psig	psig	(F)	scf/STB	Mscf/day
	1	48	0,6754	2009	680	130	51840,33	23,07
58	2	52	0,6563	2007	670	126	52465,9	25,19
	3	56	0,658	2000	680	132	55157,2	30,9
	4	56	0,645	1893	700	100	81234,7	28,431
15	5	60	0,6525	1878	750	100	76452,6	32,498
	6	64	0,6533	1847	710	100	78616,36	41,28
6	7	48	0,789	1490	670	117	87719,3	17,56
	8	52	0,79	1420	670	117	77519,38	18,44
	9	32	0,634	1317	410	82	138696,3	6,24
7	10	40	0,6326	1262	425	80	93023,26	8,369
	11	44	0,6336	1221	420	80	71326,68	9,986
	12	32	0,7554	1094	140	132	143884,9	1,307
11	13	24	0,7619	1082	92	124	181818,2	0,52
	14	16	0,7577	1052	90	118	250000	0,27
	15	40	0,82	1920	710	106	97087,38	11,38
	16	24	0,6251	6115	2595	126	100603,6	13,12
2	17	32	0,628	5910	1989	142	101936,8	22,26
	18	40	0,6344	5584	1658	156	90090,09	34,72
	19	48	0,626	5160	1452	163	88339,22	43,25
	20	40	0,7108	2207	978	140	39120	17,25
5	21	48	0,7006	2115	1005	144	39073	23,76
	22	56	0,6931	1079	1162	140	39289	29
	23	64	0,6895	1762	1218	149	39021	37,85
36	24	56	0,6524	1778	740	101	157977,9	31,1
	25	32	0,6369	2195	740	108	97087,38	15,145
17	26	38	0,6364	2184	770	113	100603,6	17,729
	27	40	0,6357	2181	780	110	101936,8	18,269
1	28	56	0,6971	2073	840	104	56211,35	32,6
30	29	56	0,6575	1431	600	124	105263,2	24,21
	30	36	0,6519	1605	360	112	107526,9	6,125
4	31	40	0,6573	1353	470	116	108695,7	16,246
	32	56	0,6596	1259	480	117	109890,1	19,261
	33	56	0,6539	1073	480	119	106383	22,824
	34	28	0,7072	3005	509	152	7575,758	7,109
146	35	32	0,7087	2877	520	158	7692,308	9,192
	36	36	0,7011	2646	530	161	7686,395	11,301
	37	40	0,6931	311	175	106	120529,7	2,42
93	38	48	0,695	297	165	107	47619,05	3,8
	39	56	0,6892	284	85	108	121506,7	4,89
	40	40	0,6933	319	182	88	93370,68	2,67
32	41	48	0,6917	314	187	89	113378,7	3,97
	42	56	0,6941	306	182	92	103305,8	5,29
	43	40	0,6931	315	170	106	32362,46	3,58
55	44	48	0,695	305	160	108	33046,93	4,9
	45	56	0,6892	290	80	110	37147,1	7,25
	46	32	0,6809	1666	435	144	93746	9,375
177	47	40	0,6771	1645	450	116	91906	13,786
	48	48	0,6825	1636	475	117	93933	21,605
	49	32	0,6941	1648	445	120	120245,7	8,78
166	50	40	0,6964	1611	460	120	120273,1	13,23
	51	48	0,7098	1534	510	117	120529,7	19,83
53	52	40	0,6754	1693	270	116	47619,05	14,04
13	53	56	0,676	1325	553	109	121506,7	20,178
	54	64	0,677	1046	551	104	93370,68	21,66
76	55	48	0,6637	1646	500	118	113378,7	19,836
	56	56	0,6653	1592	647	118	103306,8	23,959
33	57	48	0,6635	1670	553	124	79808,46	19,558
	58	56	0,6229	1650	688	125	85178,88	25,137
18	59	56	0,6726	1680	663	128	94073,38	25,02
	60	48	0,67	1606	696	128	97276,26	33,642
56	61	56	0,6754	2330	1050	136	40160,64	29,12
	62	56	0,6814	2311	1060	138	35727,05	33,83
60	63	56	0,6867	2323	1040	126	37807,18	33,43
	64	48	0,6705	2264	1038	132	32362,46	27,278
80	65	56	0,6687	2227	1078	135	33046,93	38,667
	66	48	0,6584	2306	1004	134	33738,19	25,982
	67	56	0,6586	2270	1005	135	33715,44	33,274
93	68	64	0,6597	2215	997	134	31826,86	44,559
100	69	56	0,6629	2306	1050	125	35298,27	34,767
102	70	56	0,6674	2330	1040	108	33512,06	34,18
	71	64	0,6683	2252	1130	130	37147,1	52,38
87	72	56	0,6593	2332	1100	129	36805,3	35,33
	73	48	0,6719	2345	1050	128	35026,27	31,07
79	74	56	0,6588	2322	1040	113	30581,04	34,56
104	75	56	0,6626	2217	1055	136	34458,99	32,53
	76	40	0,6627	2490	998	110	25077	17,93
56	77	48	0,662	2455	1005	111	26233	27,44
	78	56	0,6602	2393	1013	112	24890	35,02
	79	64	0,6665	2340	1142	118	26800	44,14
	80	40	0,6778	2401	1046	117	22680	15,65
97	81	48	0,6706	2372	1002	122	2885	26,83
	82	56	0,6799	2319	950	126	20240	35,68
	83	64	0,696	2216	946	131	26270	46,23
84	84	64	0,6799	2093	1170	135	21044	41,94
	85	80	0,6799	1986	1260	136	17399	55,59
	86	32	0,7166	2350	2147	120	71912	1,204
126	87	28	0,7174	2259	2048	115	71663	1,111
	88	24	0,7162	2201	1998	110	65884	0,753
109	89	66	0,6716	2258	1080	120	36496,35	34,73
88	90	56	0,6583	2235	1050	133	32122,32	33,7239
100	91	32	0,6941	1648	445	120	120245,7	8,78
78	92	40	0,6657	1651	335	109	46728,97	13,106