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Production Optimization of Water Coning Wells Using Numerical Simulation and Neural Network Modeling

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Abstract

Producing undesirable phases like water oil wells is a challenging problem in the oil industry. Water coning could be classified as one of the main reasons for that problem, as water coning is defined as a rate-sensitive phenomenon generally associated with high drawdown across the reservoirs to achieve high producing oil rates. Water coning is a near-wellbore phenomenon develops once the pressure forces drawing fluids toward the perforations overcome the buoyancy forces that segregate water from oil. This study implements Nexus simulation to build different mechanistic models with different parameters known in the literature that affect water coning formation in oil reservoirs. Simulating water coning is very challenging due to the instabilities of matrixes solvers in numerical simulators due to severe saturation change near wellbore unless very small-time steps and small grid sizes were used. The enormous number of simulation runs are used to quantify the effect of every parameter on the progress of water to form conning around the wellbore. Neural Network was built using the input and output parameters of data from the simulation runs to have a simple approach of calculation critical rate of production and how the parameter uncertainty would affect the formation of coning and finally the ultimate oil recovery.

Keywords: *water coning, critical rate, water cut performance, ANN, artificial neural network, simulation, Landmark Nexus, Petrel, Eclipse.*

1. Introduction

Production of water is one of the major problems associated with the production of hydrocarbons in the petroleum industry. An active bottom-water aquifer that supports the reservoir shall be a special case of that problem. The water production progress towards the perforations to form of the cone shape shall depend on the location, magnitude, and direction of the water movement. In reservoirs with strong bottom-water drive, oil production from the wells in these reservoirs lead to changing pressure drawdown around the wellbore, which forces oil-water contact toward the producing interval [1-2]. So, the fluid interface deforms from its initial horizontal shape into a cone shape and results in a production-related phenomenon referred to as coning [2].

Generally, the term coning is used because, in a vertical well, the shape of the interface when a well is producing the second undesirable fluid resembles an upright or inverted cone. This production phenomenon is rate sensitive and has a major challenge in the oil and gas industry. There are essentially three types of forces affecting fluid movement in the rock, these forces are capillary forces, gravity forces, and viscous forces, controlling the mechanism of formation water cone. Coning occurs when viscous forces overcome gravity forces. In oil reservoirs with bottom-water drive aquifers, during oil production, the pressure drop in the wellbore tends to draw-up water from the water zone towards the lowest producing interval at the well. The factors that affect the tendency of water to form cone are:

- Density differences between water and oil (gravitational forces).
- Fluid viscosities.

- Vertical and horizontal permeabilities.
- Distances from contacts to bottom perforations.
- Well trajectory (inclination).
- Formation dipping.
- Pressure drawdown (DP = Pr – Pwf).

Many dedicated studies gave special attention to develop correlations predicting this production rate-related problem focusing on critical rate, breakthrough time and water-cut (or water-oil ratio). The critical rate is probably the most discussed coning parameter. The main challenge from the empirical correlations that calculate the critical rate is that these correlations have been formed for specific fields and types of reservoirs which may be misleading if applied to other areas [1] .

This study focuses on building an artificial neural network (ANN) of a lot of sets of simulations runs that cover different possibilities of water coning formation in clastic reservoirs. Use the trained ANN to predict the critical rate of the investigated case then run commercial evaluation for both optimized profiles using ANN and the conventional correlation method. Figure 1 show the workflow this study followed to reach the result of identifying the critical oil rate.

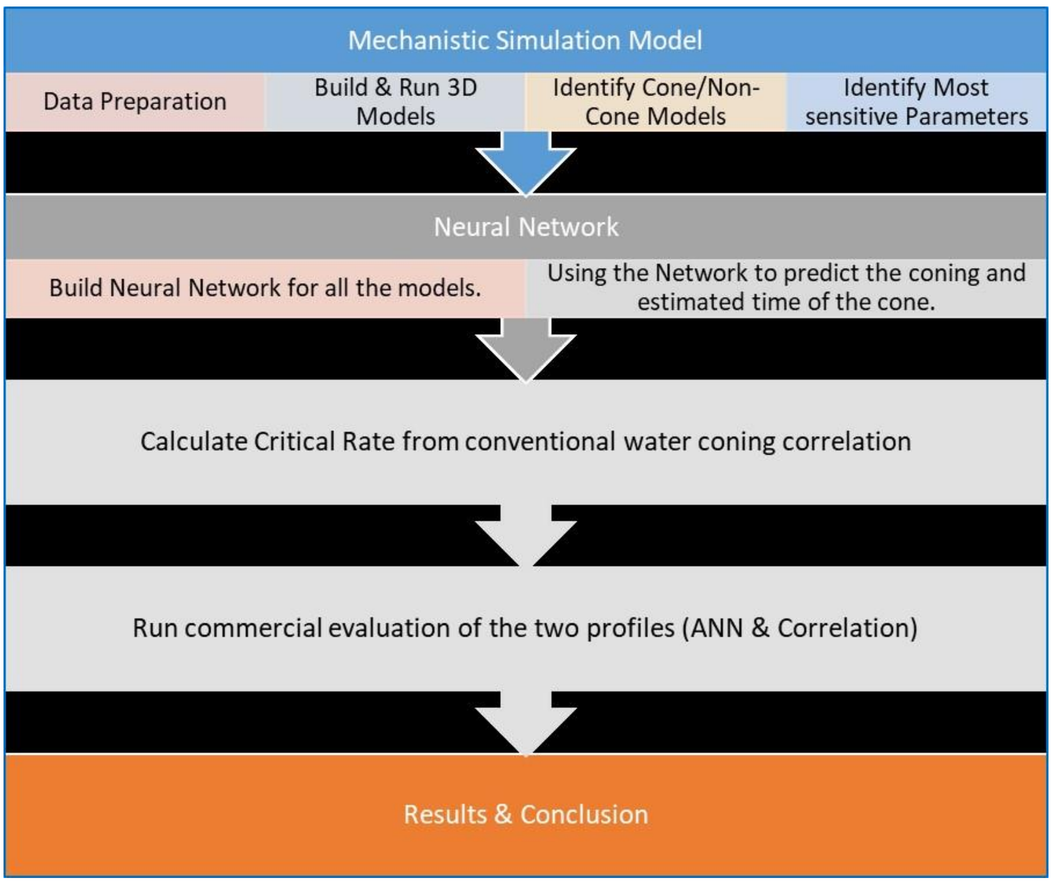


Figure 1. Study workflow

2. Reservoir characteristics

Data from 14 clastic reservoirs of bottom water drive, collected from more than 100 wells penetrated the cited reservoirs, the measured and logged data were used to build the ranges of different parameters which would be investigated in the study. Table 1 summarize the data collected for the reservoirs and shows the wide range of the parameters which would be covered through the simulation runs. Processing the previous collected data and doing basic statistics results in Table 2.

Table 1. Fields data

Field	Φavg (%)	Swi (%)	N/G (%)	Kavg (md)	Sor (%)	Pb (psi)	Tr (f)	GOR (scf/stb)	API
A	17	7	62.00	200	25	1683	265	279	27
B	17	13	60.00	500	30	1538	266	279	28.7
C	15	12	90.00	500	37	1915	280	550	30
D	17	14	30.00	500	25	1915	260	550	
E	15	8	92.00	200	37	2002	270	559	29.6
F	18	45	98.00	N/A	50	751	180	128	24
G	11	13	85.00	N/A	N/A	2000	N/A	N/A	29.5
H	14	10	90.00	200		2220	304	568	31
I	15	8	95.00	200	45	2925	304	850	38
J	15	10	91.00	452	25	3743	280	809	32
K	19	18	81.00	500	N/A	1380			34
L	13	11	92.00	25	25	4500	285	1010	32
M	17	25	96.00	500	25	4830	260	1086	32
N	15	25	96.00	500	25	4830	260	1086	32
Max	**19**	**45**	**98**	**500**	**50**	**4830**	**304**	**1086**	**38**
Average	**16**	**16**	**83**	**356**	**32**	**2588**	**268**	**646**	**31**
Min	**11**	**7**	**30**	**25**	**25**	**751**	**180**	**128**	**24**

Table 2. Reservoirs properties statistics from cores

COHK, md	
Mean	392
Standard Error	26
Median	77
Mode	11
Standard Deviation	1096
Sample Variance	1201871
Kurtosis	55
Skewness	6
Range	14000
Minimum	0
Maximum	14000
Sum	686131
Count	1749

COVK, md	
Mean	275
Standard Error	23
Median	32
Mode	0
Standard Deviation	982
Sample Variance	963630
Kurtosis	96
Skewness	9
Range	14000
Minimum	0
Maximum	14000
Sum	481824
Count	1749

COPHI, %	
Mean	15.18
Standard Error	0.08
Median	14.9
Mode	14.4
Standard Deviation	3.21
Sample Variance	10.33
Kurtosis	0.81
Skewness	0.75
Range	21.2
Minimum	10
Maximum	31.2
Sum	26554
Count	1749

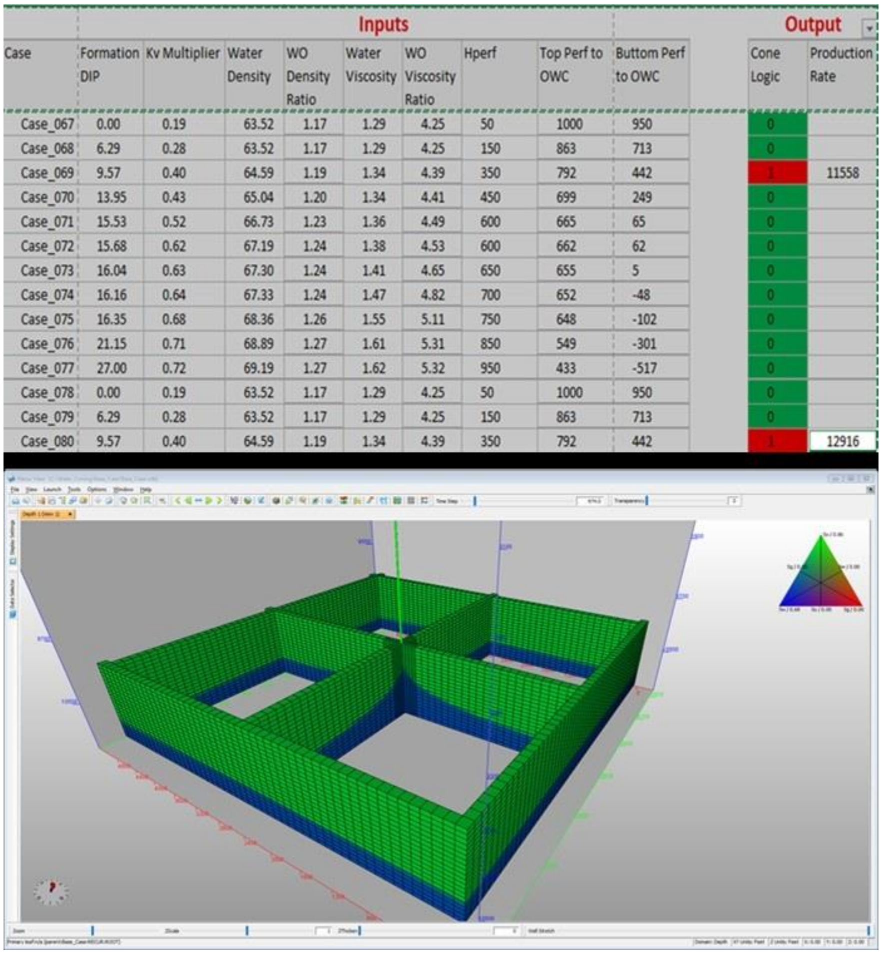
COSO, %	
Mean	49.12
Standard Error	0.62
Median	54.4
Mode	0
Standard Deviation	25.96
Sample Variance	674.07
Kurtosis	-1.18
Skewness	-0.32
Range	99.6
Minimum	0
Maximum	99.6
Sum	85914
Count	1749

COSW, $	
Mean	17.58
Standard Error	0.43
Median	11.1
Mode	0
Standard Deviation	18.02
Sample Variance	324.62
Kurtosis	1.72
Skewness	1.43
Range	89.9
Minimum	0
Maximum	89.9
Sum	30740
Count	1749

COGRD, gm/cc	
Mean	2.65
Standard Error	0
Median	2.64
Mode	2.64
Standard Deviation	0.03
Sample Variance	0
Kurtosis	#####
Skewness	17.63
Range	1.13
Minimum	2.5
Maximum	3.63
Sum	4621
Count	1747

3. Numerical simulation study

The previously processed data were used to identify base model properties in Table 3. The statistics previously calculated were used using the Monto Carlo model to generate several datasets that have been used then to generate new simulation models. These models were then investigated if a water cone was formed (Figure 2) or not. The water table continues to progress homogeneously through the lifetime of the reservoir (simulation lifetime - 20 years). Table 4 summarized the input parameters and the cone status for each simulation model.



Case	Formation DIP	Kv Multiplier	Water Density	WO Density Ratio	Water Viscosity	WO Viscosity Ratio	Hperf	Top Perf to OWC	Buttom Perf to OWC	Cone Logic	Production Rate
Inputs										Output	
Case_067	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	0	
Case_068	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	0	
Case_069	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	1	11558
Case_070	13.95	0.43	65.04	1.20	1.34	4.41	450	699	249	0	
Case_071	15.53	0.52	66.73	1.23	1.36	4.49	600	665	65	0	
Case_072	15.68	0.62	67.19	1.24	1.38	4.53	600	662	62	0	
Case_073	16.04	0.63	67.30	1.24	1.41	4.65	650	655	5	0	
Case_074	16.16	0.64	67.33	1.24	1.47	4.82	700	652	-48	0	
Case_075	16.35	0.68	68.36	1.26	1.55	5.11	750	648	-102	0	
Case_076	21.15	0.71	68.89	1.27	1.61	5.31	850	549	-301	0	
Case_077	27.00	0.72	69.19	1.27	1.62	5.32	950	433	-517	0	
Case_078	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	0	
Case_079	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	0	
Case_080	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	1	12916

Figure 2. Simulation model shows water cone formation

Table 3. Base simulation model

Property name	Value	Unit
Phi	15.2	%
K horizontal	400	md
K vertical	275	md
S_w	18	%
S_o	82	%
Rho matrix	2.65	gm/cc
Initial pressure	4,150	psi
Bubble point pressure	2441	psi
Reservoir temperature	268	F
GOR	646	SCF/STB
API	31	degree
N/G	83	%
Water salinity	180,000	PPM

3.1. Artificial neural network

Artificial neural networks (ANN) have been inspired by networks of biological neuron networks [3]. The biological nervous system is made of interconnected processing units operating in parallel, neurons are cells connected to each other and form a network [4]. ANN has been inspired by the human brain which is a complex network of biological neurons communicating with the help of each other using electrical impulses. ANNs are generally presented as systems of interconnected "neurons" organized in different layers and neurons of each layer are connected to the other utilizing weights. These interconnected "neurons" can be trained and used to compute values from inputs, and are capable of machine learning as well as pattern recognition thanks to their adaptive nature. The understanding of ANN can be made clear by understanding the functioning of biological neuron networks.

ANN is defined as a computer model that attempts to mimic the neural network of a human brain and simulate the specific processing of the human nervous system. It is an adaptive system that establishes a specific relation between the input and output. The typical ANN can be illustrated as in Figure 3, the architecture of any neural network would be formed from the input layer (input parameter), several hidden layers according to the problem under investigation and finally the output layer.

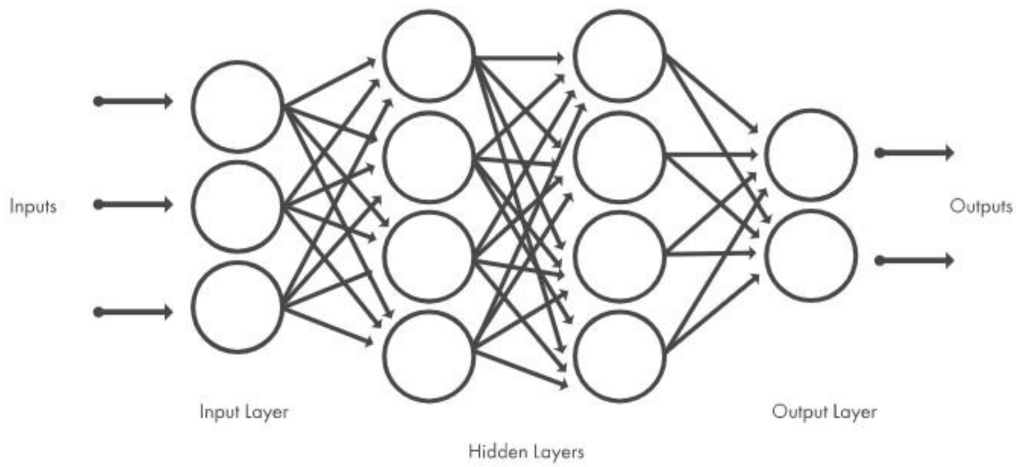


Figure 3. Typical neural network architecture

Consider m number of inputs (X1, X2, X3, ..., Xn) to neuron m as shown in Figure 4. The weights connecting n number of inputs to mth neuron are represented by:

$$[\boldsymbol{W}] = [\boldsymbol{Wm1}, \boldsymbol{Wm2}, \boldsymbol{Wm3}, \dots\dots, \boldsymbol{Wmn}] \qquad (1)$$

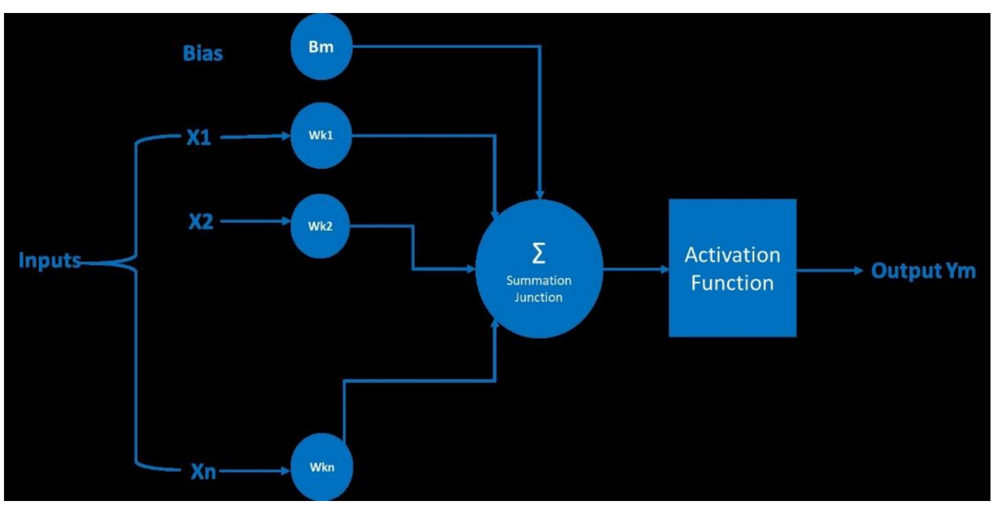


Figure 4. ANN hidden layer

The summation function or summing junction is to function used to sum all the inputs multiplied by their corresponding weights. There is also the activation function which makes the neuron to produce a specific output only if it exceeds a threshold value. The transfer function (output of m neuron) can be expressed as in Equation I

$$Ym = \sum_{n=1}^{n} X_n . W_{mn} + Bm \qquad (2)$$

3.2. Network architecture

A feed-forward backpropagation network was designed for this purpose. Levenberg-Marquardt optimization technique was used for updating the bias and weights during training. The optimum architecture for the water coning identification was determined on a trial and error basis. These trial and error parameters under discussion are [5]:

- Training function
- Adaption learning function
- Transfer function
- Error Function
- Number of hidden layers
- Number of neurons in each layer

The selection of optimum neurons number in every layer would reflect the complexity of the cited problem under discussion. Where, if the selected number is too few the ANN will not converge to minimum error while training the network and if the number was too high the network will be overfitting the input datasets and will poorly predict the new cases (Figure 5).

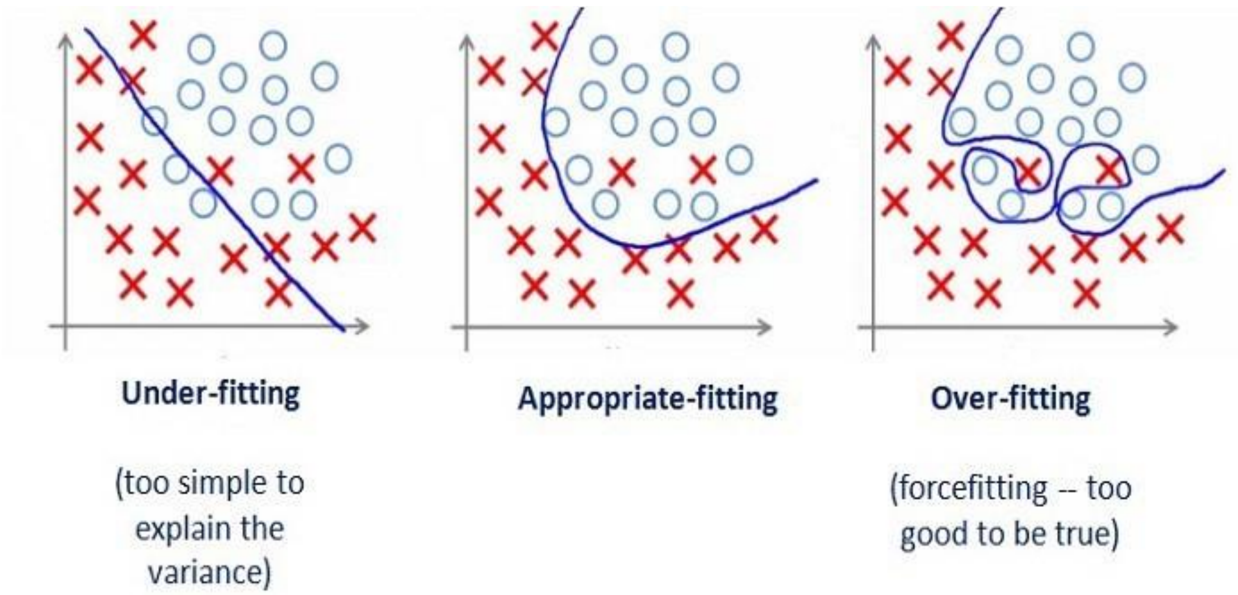


Figure 5. Data Fitting in ANNs

3.3. Water coning artificial neural network

Ten input parameters were elected to be used for water coining AAN model:

Production rate	Water viscosity
Formation DIP	WO viscosity ratio
k_v/k_h multiplier	H.perf
Water density	Top Perf to OWC
WO density ratio	Bottom Perf to OWC

The only output of the ANN model will be a logical output (Boolean type - Yes or No). Boolean Variable is a data type that has one of two possible values (usually true or false) [6]. It is to represent the two truth values of logic and Boolean algebra.

MathWorks Matlab programming language is used for the suggested supervised neural network which is trained to produce the output of cone to be true in response to sample input datasets which showed the formation of the cone during the lifetime of the simulation run. These datasets were extracted from the uncertainty and sensitivity runs of simulation models.

Different models were designed, trained and validated and based on the training and validation curves. The most suitable one was selected to be used; for the sack of illustration, a simple ANN model and the selected suitable model are presented in Figure 6 and Figure 7 respectively.

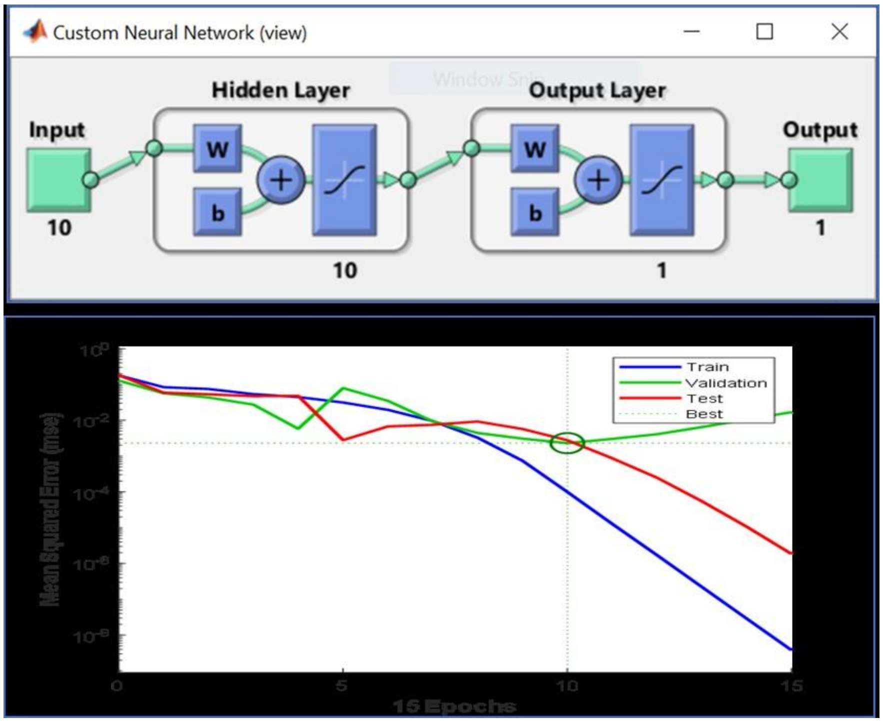


Figure 6. ANN Model 1 “Simple - 1 hidden layer”

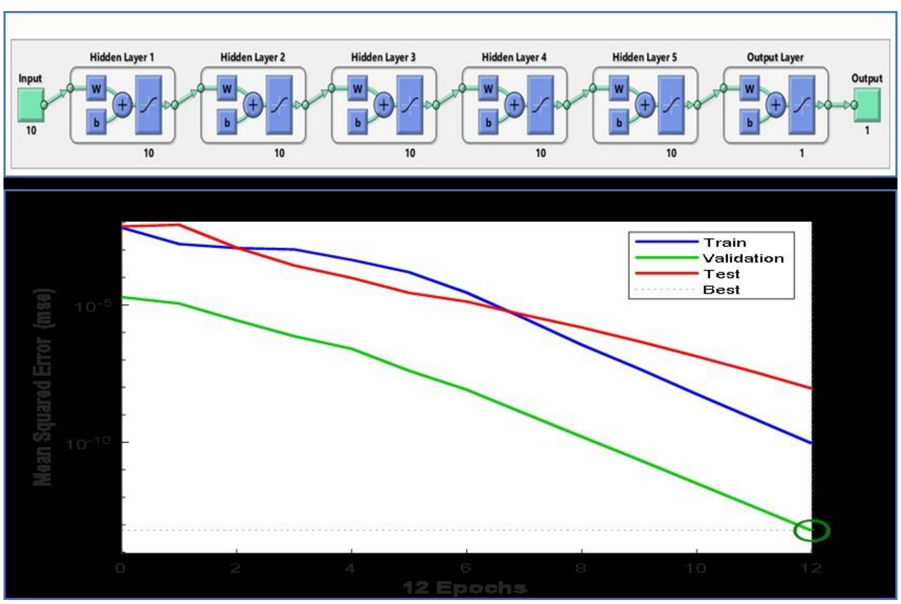


Figure 7. ANN Model 2 “Optimized - 5 hidden layers”

3.4. Field application and commercial evaluation

3.4.1. Field H

Field H is located in an offshore marine environment. One of its main reservoirs is the reservoir "N" which is sandstone fluvial marine formation with good pressure support from a strong to medium bottom water aquifer. This reservoir under consideration is very homogenous with a very thick pay zone that can reach up to 1,000 ft of net pay which makes it a candidate to form a water cone under suitable drawdown condition. Table 5 show the reservoir properties for the above-cited field.

Table 5. Field H properties

Property	Value	Units	Property	Value	Units
Formation DIP	15.0	degree	WO viscosity ratio	1.25	fraction
Kv multiplier	0.83	fraction	H perf	105.0	ft
Water density	1.05	lb/ft^3	Top Perf to OWC	195.0	ft
WO density ratio	1.5	fraction	Bottom Perf to OWC	90.0	ft
Water viscosity	0.36	cp			

The well under investigation was already drilled and completed in the reservoir and produces naturally. The well was capable of delivering a maximum of 3,000 BOPD with 25% WC with the help of a gas lift system as the used type of artificial lift method.

3.4.2. Commercial evaluation

In house commercial evaluation tool was programmed to perform full commercial and economical studies. The application was designed on the interface of Microsoft Excel for the ease of use and programmed using visual basic for applications (VBA). The tool was validated in many cases against commercial software packages in the market and had nearly matched results.

The software performs a commercial evaluation for the production sharing agreement (PSA). The Field was cover with the agreement of the cited below parameters:

Working interest	75.00	%	OPEX recovery	100.00	%/year
Royalty	15.00	%	Excess share	0.00	%
Cost recovery limit	40.00	%	Production share	20.00	%
CAPEX recovery	20.00	%/year			

The discount rate was selected to be 10 %/year and all the money was discounted to the start date of the project.

3.4.3. Correlation profile commercial evaluation

Using conventional correlation which predicts the critical rate that would result in forming a water cone around the wellbore, showed the critical rate will be equivalent to 1,200 BOPD. The commercial evaluation corresponding to the profile of 1,200 BOPD is shown in Figure 8. The result summary was as cited below:

CAPEX	0	MM $
OPEX	11.877	MM $
Total expenditure	11.877	MM $
Cost eecovered	11.304	MM $
Profit oil	9.184	MM $
Revenue	20.488	MM $
Net profit (NPV)	8.611	MM $
Payout time	4	Months
Max exposure	-0.038	MM $
Economic limit	8.6@Dec.29	MM $
DPI (NCF/NPC)	72.5	%
UTC (Cost/BBL)	5.914	$/BBL
Break-Even price	22.0	%
IRR	1050.1	%/year

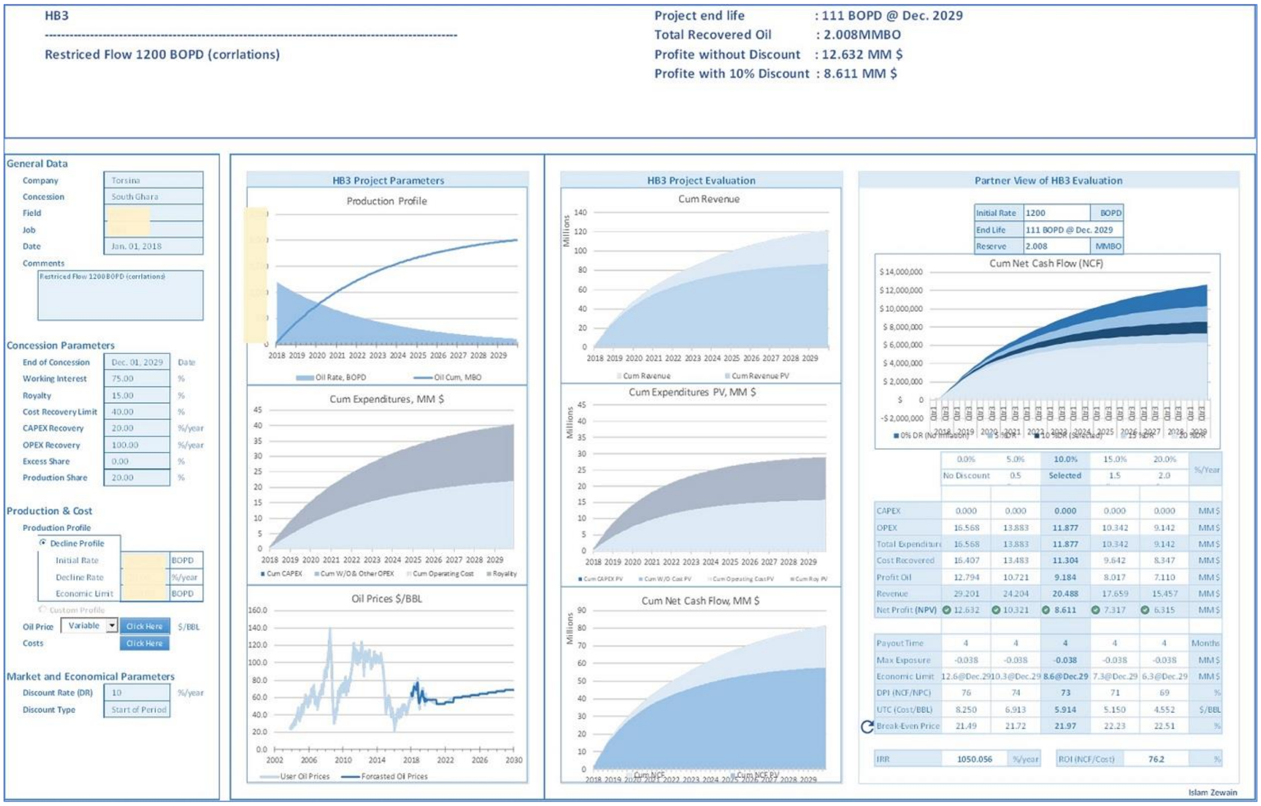


Figure 8. Commercial evaluation of correlation profile

3.4.4. ANN profile commercial evaluation

The trained and validated ANN Model 2 was used to test the formation of cone formation up to the maximum rate the reservoir can deliver 3,000 BOPD with up to 50% WC. The model confirmed that the water table would progress in smooth movement toward the perforations and will not form a water cone under the examined condition. The commercial evaluation corresponding to that profile of 3,000 BOPD showed in Figure 9. The result summary was as cited below:

CAPEX	0.000	MM $
OPEX	18.208	MM $
Total expenditure	18.208	MM $
Cost recovered	17.341	MM $
Profit oil	14.264	MM $
Revenue	31.605	MM $
Net profit (NPV)	13.397	MM $
Payout time	4	Months
Max exposure	-0.094	MM $
Economic limit	13.4@Aug.26	MM $
DPI (NCF/NPC)	73.6	%
UTC (Cost/BBL)	6.755	$/BBL
Break-Even price	23.0	%
IRR	1046.1	%/year

Figure 9. Commercial evaluation of ANN profile

4. Recommendations and conclusions

The authors work on a more complex model by covering more parameters of the reservoir and production strategy to cover a wide space of probabilities. This would affect the ANN to be more accurate and time-sensitive as it would predicate the cone progress with time.

Finally, this paper recommends having further studies of fields, which may face the problem of water coning by simulation model or artificial neural network using data of the nearby fields. This ANN model would serve as a new customized correlation for the offset fields as the use of correlation may give aggressive critical oil production values.

Acronyms

ANN	*Artificial Neural Network*	*OPEX*	*Operating Expenditures*
VBA	*Visual Basic for Applications*	*NPV*	*Net Present Value*
BOPD	*Barrel Oil Per Day*	*DPI*	*Discounted Profit to Investment*
WC	*Water Cut*	*NCF*	*Net Cash Flow*
PSA	*Production Sharing Agreement*	*NPC*	*Net Present Cost*
CAPEX	*Capital Expenditures*	*UTC*	*Unit Technical Cost*
IRR	*Internal Rate of Return*		

Table 4. Simulation runs datasets and output

Case	Production Rate BOPD	Formation DIP,degree	Kv Multiplier, fraction	Water Density, lb/ft3	WO Density Ratio, fraction	Water Viscosity,cp	WO Viscosity Ratio, fraction	H-Perf, ft	Top Perf to OWC, ft	Bottom Perf to OWC, ft	Cone Logic, Yes/No
Case_001	500	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	No
Case_002	500	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	No
Case_003	500	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	No
Case_004	500	13.95	0.43	65.04	1.20	1.34	4.41	450	699	249	No
Case_005	500	15.53	0.52	66.73	1.23	1.36	4.49	600	665	65	No
Case_006	500	15.68	0.62	67.19	1.24	1.38	4.53	600	662	62	No
Case_007	500	16.04	0.63	67.30	1.24	1.41	4.65	650	655	5	No
Case_008	500	16.16	0.64	67.33	1.24	1.47	4.82	700	652	-48	No
Case_009	500	16.35	0.68	68.36	1.26	1.55	5.11	750	648	-102	No
Case_010	500	21.15	0.71	68.89	1.27	1.61	5.31	850	549	-301	No
Case_011	500	27.00	0.72	69.19	1.27	1.62	5.32	950	433	-517	No
Case_012	4318	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	No
Case_013	4318	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	No
Case_014	4318	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	No
Case_015	4318	13.95	0.43	65.04	1.20	1.34	4.41	450	699	249	No
Case_016	4318	15.53	0.52	66.73	1.23	1.36	4.49	600	665	65	No
Case_017	4318	15.68	0.62	67.19	1.24	1.38	4.53	600	662	62	No
Case_018	4318	16.04	0.63	67.30	1.24	1.41	4.65	650	655	5	No
Case_019	4318	16.16	0.64	67.33	1.24	1.47	4.82	700	652	-48	No
Case_020	4318	16.35	0.68	68.36	1.26	1.55	5.11	750	648	-102	No
Case_021	4318	21.15	0.71	68.89	1.27	1.61	5.31	850	549	-301	No
Case_022	4318	27.00	0.72	69.19	1.27	1.62	5.32	950	433	-517	No
Case_023	6099	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	No
Case_024	6099	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	No
Case_025	6099	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	No
Case_026	6099	13.95	0.43	65.04	1.20	1.34	4.41	450	699	249	No
Case_027	6099	15.53	0.52	66.73	1.23	1.36	4.49	600	665	65	No
Case_028	6099	15.68	0.62	67.19	1.24	1.38	4.53	600	662	62	No
Case_029	6099	16.04	0.63	67.30	1.24	1.41	4.65	650	655	5	No
Case_030	6099	16.16	0.64	67.33	1.24	1.47	4.82	700	652	-48	No
Case_031	6099	16.35	0.68	68.36	1.26	1.55	5.11	750	648	-102	No
Case_032	6099	21.15	0.71	68.89	1.27	1.61	5.31	850	549	-301	No
Case_033	6099	27.00	0.72	69.19	1.27	1.62	5.32	950	433	-517	No
Case_034	7584	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	No
Case_035	7584	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	No

Case	Production Rate BOPD	Formation DIP,degree	Kv Multiplier, fraction	Water Density, lb/ft3	WO Density Ratio, fraction	Water Viscosity,cp	WO Viscosity Ratio, fraction	H-Perf, ft	Top Perf to OWC, ft	Bottom Perf to OWC, ft	Cone Logic, Yes/No
Case_036	7584	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	No
Case_037	7584	13.95	0.43	65.04	1.20	1.34	4.41	450	699	249	No
Case_038	7584	15.53	0.52	66.73	1.23	1.36	4.49	600	665	65	No
Case_039	7584	15.68	0.62	67.19	1.24	1.38	4.53	600	662	62	No
Case_040	7584	16.04	0.63	67.30	1.24	1.41	4.65	650	655	5	No
Case_041	7584	16.16	0.64	67.33	1.24	1.47	4.82	700	652	-48	No
Case_042	7584	16.35	0.68	68.36	1.26	1.55	5.11	750	648	-102	No
Case_043	7584	21.15	0.71	68.89	1.27	1.61	5.31	850	549	-301	No
Case_044	7584	27.00	0.72	69.19	1.27	1.62	5.32	950	433	-517	No
Case_045	8942	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	No
Case_046	8942	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	No
Case_047	8942	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	No
Case_048	8942	13.95	0.43	65.04	1.20	1.34	4.41	450	699	249	No
Case_049	8942	15.53	0.52	66.73	1.23	1.36	4.49	600	665	65	No
Case_050	8942	15.68	0.62	67.19	1.24	1.38	4.53	600	662	62	No
Case_051	8942	16.04	0.63	67.30	1.24	1.41	4.65	650	655	5	No
Case_052	8942	16.16	0.64	67.33	1.24	1.47	4.82	700	652	-48	No
Case_053	8942	16.35	0.68	68.36	1.26	1.55	5.11	750	648	-102	No
Case_054	8942	21.15	0.71	68.89	1.27	1.61	5.31	850	549	-301	No
Case_055	8942	27.00	0.72	69.19	1.27	1.62	5.32	950	433	-517	No
Case_056	10250	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	No
Case_057	10250	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	No
Case_058	10250	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	No
Case_059	10250	13.95	0.43	65.04	1.20	1.34	4.41	450	699	249	No
Case_060	10250	15.53	0.52	66.73	1.23	1.36	4.49	600	665	65	No
Case_061	10250	15.68	0.62	67.19	1.24	1.38	4.53	600	662	62	No
Case_062	10250	16.04	0.63	67.30	1.24	1.41	4.65	650	655	5	No
Case_063	10250	16.16	0.64	67.33	1.24	1.47	4.82	700	652	-48	No
Case_064	10250	16.35	0.68	68.36	1.26	1.55	5.11	750	648	-102	No
Case_065	10250	21.15	0.71	68.89	1.27	1.61	5.31	850	549	-301	No
Case_066	10250	27.00	0.72	69.19	1.27	1.62	5.32	950	433	-517	No
Case_067	11558	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	No
Case_068	11558	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	No
Case_069	11558	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	Yes
Case_070	11558	13.95	0.43	65.04	1.20	1.34	4.41	450	699	249	No
Case_071	11558	15.53	0.52	66.73	1.23	1.36	4.49	600	665	65	No

Case	Production Rate BOPD	Formation DIP,degree	Kv Multiplier, fraction	Water Density, lb/ft3	WO Density Ratio, fraction	Water Viscosity,cp	WO Viscosity Ratio, fraction	H-Perf, ft	Top Perf to OWC, ft	Bottom Perf to OWC, ft	Cone Logic, Yes/No
Case_072	11558	15.68	0.62	67.19	1.24	1.38	4.53	600	662	62	No
Case_073	11558	16.04	0.63	67.30	1.24	1.41	4.65	650	655	5	No
Case_074	11558	16.16	0.64	67.33	1.24	1.47	4.82	700	652	-48	No
Case_075	11558	16.35	0.68	68.36	1.26	1.55	5.11	750	648	-102	No
Case_076	11558	21.15	0.71	68.89	1.27	1.61	5.31	850	549	-301	No
Case_077	11558	27.00	0.72	69.19	1.27	1.62	5.32	950	433	-517	No
Case_078	12916	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	No
Case_079	12916	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	No
Case_080	12916	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	Yes
Case_081	12916	13.95	0.43	65.04	1.20	1.34	4.41	450	699	249	No
Case_082	12916	15.53	0.52	66.73	1.23	1.36	4.49	600	665	65	No
Case_083	12916	15.68	0.62	67.19	1.24	1.38	4.53	600	662	62	No
Case_084	12916	16.04	0.63	67.30	1.24	1.41	4.65	650	655	5	No
Case_085	12916	16.16	0.64	67.33	1.24	1.47	4.82	700	652	-48	No
Case_086	12916	16.35	0.68	68.36	1.26	1.55	5.11	750	648	-102	No
Case_087	12916	21.15	0.71	68.89	1.27	1.61	5.31	850	549	-301	No
Case_088	12916	27.00	0.72	69.19	1.27	1.62	5.32	950	433	-517	No
Case_089	14401	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	No
Case_090	14401	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	Yes
Case_091	14401	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	Yes
Case_092	14401	13.95	0.43	65.04	1.20	1.34	4.41	450	699	249	No
Case_093	14401	15.53	0.52	66.73	1.23	1.36	4.49	600	665	65	No
Case_094	14401	15.68	0.62	67.19	1.24	1.38	4.53	600	662	62	No
Case_095	14401	16.04	0.63	67.30	1.24	1.41	4.65	650	655	5	No
Case_096	14401	16.16	0.64	67.33	1.24	1.47	4.82	700	652	-48	No
Case_097	14401	16.35	0.68	68.36	1.26	1.55	5.11	750	648	-102	No
Case_098	14401	21.15	0.71	68.89	1.27	1.61	5.31	850	549	-301	No
Case_099	14401	27.00	0.72	69.19	1.27	1.62	5.32	950	433	-517	No
Case_100	16182	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	No
Case_101	16182	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	Yes
Case_102	16182	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	Yes
Case_103	16182	13.95	0.43	65.04	1.20	1.34	4.41	450	699	249	No
Case_104	16182	15.53	0.52	66.73	1.23	1.36	4.49	600	665	65	No
Case_105	16182	15.68	0.62	67.19	1.24	1.38	4.53	600	662	62	No
Case_106	16182	16.04	0.63	67.30	1.24	1.41	4.65	650	655	5	No
Case_107	16182	16.16	0.64	67.33	1.24	1.47	4.82	700	652	-48	No

Case	Production Rate BOPD	Formation DIP,degree	Kv Multiplier, fraction	Water Density, lb/ft3	WO Density Ratio, fraction	Water Viscosity,cp	WO Viscosity Ratio, fraction	H-Perf, ft	Top Perf to OWC, ft	Bottom Perf to OWC, ft	Cone Logic, Yes/No
Case_108	16182	16.35	0.68	68.36	1.26	1.55	5.11	750	648	-102	No
Case_109	16182	21.15	0.71	68.89	1.27	1.61	5.31	850	549	-301	No
Case_110	16182	27.00	0.72	69.19	1.27	1.62	5.32	950	433	-517	No
Case_111	20000	0.00	0.19	63.52	1.17	1.29	4.25	50	1000	950	No
Case_112	20000	6.29	0.28	63.52	1.17	1.29	4.25	150	863	713	Yes
Case_113	20000	9.57	0.40	64.59	1.19	1.34	4.39	350	792	442	Yes
Case_114	20000	13.95	0.43	65.04	1.20	1.34	4.41	450	699	249	Yes
Case_115	20000	15.53	0.52	66.73	1.23	1.36	4.49	600	665	65	No
Case_116	20000	15.68	0.62	67.19	1.24	1.38	4.53	600	662	62	No
Case_117	20000	16.04	0.63	67.30	1.24	1.41	4.65	650	655	5	No
Case_118	20000	16.16	0.64	67.33	1.24	1.47	4.82	700	652	-48	No
Case_119	20000	16.35	0.68	68.36	1.26	1.55	5.11	750	648	-102	No
Case_120	20000	21.15	0.71	68.89	1.27	1.61	5.31	850	549	-301	No
Case_121	20000	27.00	0.72	69.19	1.27	1.62	5.32	950	433	-517	No

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