Bottom-up optimization approach and nonlinear model for oilfield output programming

Yongchi Ma\(^1\) \(^*\), Bao Xi\(^1\), Shaohui Dong\(^1\), Xuening Chen\(^2\)

\(^1\) School of Management, Harbin Institute of Technology, Harbin, 150001, Heilongjiang, P. R. China
\(^2\) Faculty of resources, China University of Geosciences, Wuhan, 430074, Hubei, P. R. China

(Received April 28 2007, Accepted October 17 2007)

Abstract. In the process of oilfield development, it is unable to separate the marginal effect of each developing measure from the aggregate effect of all developing measures, so both marginal analysis method and Markowitz portfolio theory are helpless for the oilfield output programming. Function Simulation is proved to be a feasible tool to model the input-output relationship of oilfield development. By training with historical development data, it possesses extrapolation capability in some range, which forms the basis for the oilfield output programming. The purpose of this paper is to report on the use of bottom-up optimization mechanism which is embedded by Function Simulation to optimize the distribution of output in oilfield. Following presentation of the features of oilfield development, the top-down approach and the Function Simulation as a tool for oilfield output programming are reviewed. The process of designing the bottom-up optimization framework embedded with Function simulations, determining the embedding protocol and coordinating the corresponding relationship between the subentry outputs and the subentry costs is described. Subsequently, models and an example are given. Finally, the paper concludes that above optimization method is suitable to solve a class of programming problems.

Keywords: nonlinear optimization, bottom-up, output programming, function Simulation

1 Introduction

Oilfield development is a dynamic complex system. In generally, oil output is divided into natural output, stimulation output and new well output. An advantage of this division is easy to measure the corresponding costs of each subentry output, which are called maintenance cost, stimulation cost, and investment. However, the volume of each subentry output is unable to measure directly, and in generally they are made certain by calculation. The direct reason is that the oil reservoir is underground and like a black box leads to the process of oil extraction invisible, and the indirectly reason is that the subentry outputs affect each other. For example, when an oil well is given a stimulation measure, its oil output will increase (stimulation output increase), but the output of other wells nearby maybe decrease (natural output decrease). Viewed from the system perspective, oil reservoir is a connected system, and its inner state is maybe changed by any developing measure, which affects other wells in turn. Hence, the oilfield development and the oil output possess the features as followings:

· The aggregate annual output of a reservoir (or block, oilfield) can be accurately measured
· The aggregate output consists of three subentry outputs (natural output, stimulation output and new well output); the corresponding subentry costs are maintenance cost, stimulation cost, and investment. Each subentry cost can be accurately measured while each subentry output only can be made certain by calculation indirectly

\(^*\) Corresponding author. Tel: +86-451-86401007
E-mail address: frigo8341@163.com.
On the reservoir scale, the calculation value of the subentry outputs are relatively correct; lower this scale, their precision is uncertain

- The subentry outputs affect each other, not independent
- The marginal effect of each developing measure can’t be separated from the aggregate effect of all developing measures

The core task of oilfield development programming is to make certain and optimize the aggregate output, each subentry output and the structure of stimulation measures on the block (reservoir) scale in the next year in an oilfield. As the features mentioned above, both marginal analysis method and Markowitz portfolio theory are helpless for this task. In recent years, Function Simulation is proved to be a feasible tool to model the input-output relationship of oilfield development. By training with historical development data, it possesses extrapolation capability in some range, which forms the basis for the oilfield output programming. The accuracy of oilfield output programming depends on the accuracy of Function Simulation, and the extrapolation capability of Function Simulation depends on its structure. Hence, the key to improve the accuracy of oilfield output programming (Function simulation) depends on:

- Open the black box (oilfield development system) and divide it into several small black boxes
- Apply Function Simulation for each small black box
- Structure the relationships among the Function simulations according to the relationships among the small black boxes

The purpose of this paper is to report on the use of bottom-up optimization mechanism which is embedded by Function Simulation to optimize the distribution of output in oilfield. Following presentation of the features of oilfield development, the top-down approach and the Function Simulation as a tool for oilfield output programming are reviewed. The process of designing the bottom-up optimization framework embedded with Function simulations, determining the embedding protocol and coordinating the corresponding relationship between the subentry outputs and the subentry costs is described. Subsequently, models and an example are given. Finally, the paper concludes that above optimization method is suitable to solve a class of programming problems.

2 Literature review

Since the 1980s, in China, both the oilfields and relative universities have intensive researches on the oilfield development programming. For example, Daqing oilfield has optimized the development indices during the 7th, 8th and 9th Five-years Periods respectively by using linear programming and dynamic programming, and Shengli oilfield introduced the non-linear & multi-objective model on the same problem during the 9th Five-year Period. Undoubtedly, these researches have been playing an active role in the rapid progress for the formulation of development planning, but these researches all employ the top-down approach and take the development indices as the point of reference. There are some obvious limitations such as poor description of complex correlative relationship between output and cost, as well as the weak convergence of algorithm.

In the modeling of output programming, the most important is to describe the relationship between output and cost. In the oilfield development, they are both decided by the composition of reservoir state and developing measures (see Fig. 1). The corresponding relationship between output and the composition of its influencing factors is 1 : n (one-to-multi), because the different compositions may lead to the same output. According to the same principle, the relationship between cost and the composition is also 1 : n (one-to-multi). So the relationship between the output and the cost is a complex mapping relationship of n : n (multi-to-multi). Hence, in order to describe the correlative relationship clearly, we must describe the two relationships 1 : n at the same time. Dawson Robert et al want to establish the direct correlative relationship between output and cost for the oilfield output programming. Obviously, this solution is unfeasible and the outcome lack reliability.

Function Simulation is proved to be an effective method to describe the relationship between the development index and its factors. It been successfully applied to local optimization problem in oilfield development,
like the optimal structure problem of stimulation measures. But in the globally optimal problem of oilfield output programming, up to now, it has not still described the complex mapping relationship clearly. Liu Zhibin et al\cite{6, 13} describe this relationship by taking the cost as a part of input (treat as an influencing factor of oil output) (see Fig. 2). But obviously, this method neglected the correlative relationship between cost and the other factors (such as composition of stimulation measures), which will lead to the potential conflicts of taking value between the cost and the other factors. In essence, this method only described one 1: n relationship of the two. So this Function Simulation, viewed from the methodology perspective, is hard to possess the extrapolation ability.

According to above analysis, we need use two n : 1 relationships to describe the complex correlative relationship (n : n) between the important development indices. That is to say, we need employ the composition of Function Simulation, and at the same time, we need to find a modeling mechanism to eliminate the potential conflict of taking value in input. The traditional top-down modeling mechanism seems difficult to avoid this conflict; on the contrary, the bottom-up modeling mechanism can do it well.

3 Research design

This research tries to optimize output distribution among the oil extraction factories in an oilfield, and at the same time make certain the composition of the subentry oil output in each oil extraction, under taking into account of oilfield natural state, economic profit, and output goals set by superior company. It involves three key questions:

· model design must ensure corresponding relation between output and cost.
· to describe the non-linear relative relationship between development indices (such as output and cost) and theirs influence factors
· to find a good algorithm to calculate the non-linear programming model

Viewed from the system perspective, the developer imposes some developing measures on the oilfield which like a big black box to get oil output. And at the same time, some development indices which reflect the part state of the oilfield are measured to support the decision of next developing measure. So, according to the experience and principle of oilfield development, the big black box can be divided into several small
black boxes and state variables, and further restructure the input-output relationship of oilfield development (see Fig. 3).

Fig. 3. Opening up the black box to some extent

In the process of structuring, a bottom-up modeling approach which is embedded with Function Simulations is employed (see Fig. 4). Combined with the evolution computation, this approach can avoid the potential conflict of taking value among the different Function Simulations.

- identifying the development indices and their influencing factors according to the optimization objectives and oilfield development principle, and further screen out the important influence factors by quantitative index analytical method (such as statistic analysis).

- taking the controllable influence factors which chosen from the influence factors as direct decision variables and taking the long-time scale influence factors as constant, then establish the input-output relationships between development indices and their influence factors by Function Simulation.

- taking the correlative relationships as constraint condition, the controllable influence factors as decision variables, and taking the development index as dependent variables, and then establish the optimization model. This model can ensure the corresponding among the development indices.

- to solve the optimization model by evolution algorithm.

Fig. 4. Research framework

*MSEM email for contribution: submit@msem.org.uk*
4 Solution

4.1 Index analysis

The optimization objectives, the development indices and their factors are identified according to the theory and the past experience of oilfield development.

- Objectives: output maximum, cost minimum, profit maximum
- Development indices: natural output, stimulation output, new well output, maintenance cost, stimulation cost, investment
- Important factors: number of working oil well ($U_{x1}$), average working time of oil well ($U_{x2}$), number of working water well ($U_{x3}$), average volume of water injection ($U_{x4}$); used reserves ($S_1$), recovery degree of recoverable reserves ($S_2$), hydrous rate ($S_3$), accumulated remaining recoverable reserves ($S_4$); workloads of fracturing ($U_{x5}$), acidification ($U_{x6}$), overhaul ($U_{x7}$), perforation ($U_{x8}$), profile adjustment ($U_{x9}$), water plugging ($U_{x10}$), the others stimulation measures ($U_{x11}$); number of new well ($U_{x12}$)

The correlative structure of above variables is shown in Fig. 5.

![Fig. 5. Correlative structure of variables](image)

4.2 Function simulation

According to Fig. 5 and dynamic change laws of historic development, establish the correlative relationships between development indices of each block and their influence factors by use of the Function Simulation (refer to literatures [8, 11]) as following:

$$X^{(k)}_{iz} = X^{(k)}_{iz} [U^{(k)}_{iz1}, U^{(k)}_{iz2}, U^{(k)}_{iz3}, U^{(k)}_{iz4}, S^{(k)}_{i1}, S^{(k)}_{i2}, S^{(k)}_{i3}, S^{(k)}_{i4}] \quad (1)$$

$$C^{(k)}_{iz} = C^{(k)}_{iz} [U^{(k)}_{iz1}, U^{(k)}_{iz2}, U^{(k)}_{iz3}, U^{(k)}_{iz4}, S^{(k)}_{i1}, S^{(k)}_{i2}, S^{(k)}_{i3}, S^{(k)}_{i4}] \quad (2)$$

$$X^{(k)}_{ic} = X^{(k)}_{ic} [U^{(k)}_{ic1}, U^{(k)}_{ic2}, U^{(k)}_{ic3}, U^{(k)}_{ic4}, U^{(k)}_{ic5}, U^{(k)}_{ic6}, U^{(k)}_{ic7}, S^{(k)}_{i1}, S^{(k)}_{i2}, S^{(k)}_{i3}, S^{(k)}_{i4}] \quad (3)$$

$$X^{(k)}_{ic} = X^{(k)}_{ic} [U^{(k)}_{ic1}, U^{(k)}_{ic2}, U^{(k)}_{ic3}, U^{(k)}_{ic4}, U^{(k)}_{ic5}, U^{(k)}_{ic6}, U^{(k)}_{ic7}, S^{(k)}_{i1}, S^{(k)}_{i2}, S^{(k)}_{i3}, S^{(k)}_{i4}] \quad (4)$$

$$X^{(k)}_{iz} = X^{(k)}_{iz} [U^{(k)}_{iz1}, S^{(k)}_{i1}, S^{(k)}_{i2}, S^{(k)}_{i3}, S^{(k)}_{i4}] \quad (5)$$

$$I^{(k)}_{iz} = I^{(k)}_{iz} [U^{(k)}_{iz1}, S^{(k)}_{i1}, S^{(k)}_{i2}, S^{(k)}_{i3}, S^{(k)}_{i4}] \quad (6)$$
Where:

\( X^{(k)}_{iz} \): natural output of \( i \) block in \( k \) year
\( C^{(k)}_{iz} \): maintenance cost of \( i \) block in \( k \) year
\( X^{(k)}_{ic} \): stimulation output of \( i \) block in \( k \) year
\( C^{(k)}_{ic} \): stimulation measure cost of \( i \) block in \( k \) year
\( X^{(k)}_{ix} \): new well output of \( i \) block in \( k \) year
\( I^{(k)}_{ix} \): investment of \( i \) block in \( k \) year
\( U \): controllable influence factors
\( S \): uncontrollable influence factors

\( U^{(k)}_{iz1} - U^{(k)}_{iz4} \): number of working oil well, average working time of oil well, number of working water well and average water injection of \( i \) block in \( k \) year

\( U^{(k)}_{ic1} - U^{(k)}_{ic7} \): workloads of seven measures which can improve output in \( i \) block in \( k \) year

\( U^{(k)}_{ix1} \): number of new well of \( i \) block in \( k \) year

\( S^{(k)}_{i1} - S^{(k)}_{i4} \): used reserves, recovery degree of recoverable reserves, hydrous rate, accumulated remaining recoverable reserves.

Above Function Simulations are combined according to the embedding protocol as following (see Fig. 6).

Fig. 6. The structure of Function Simulation combination

The combination of Function Simulations can be expressed together as:

\[
Z^{(l)} = Z^{(l)}[U, S], l = 1, 2, \ldots, 6
\]  

(7)

4.3 Model

As is known to all, three factors necessary to set up an optimization model are: (1) decision variables, (2) objectives, (3) constraint conditions. The decision variables for the above question are clearly the development indices of each subordinate unit. But these indices are changing with their influence factors. Therefore the true decision variables are the controllable influence factors of each subordinate unit’s development indices which are dependent variables.

Model I Output maximum

\[
J_1 = \max \left[ \sum_{i=1}^{n} \left( X^{(k)}_{iz} + X^{(k)}_{ic} + X^{(k)}_{ix} \right) \right]
\]  

(8)
Subject to

\[ \sum_{i=1}^{n} (X_{iz}^{(k)} + X_{ic}^{(k)} + X_{ix}^{(k)}) \geq A(k) \] (9)

\[ \sum_{i=1}^{n} (C_{iz}^{(k)} + C_{ic}^{(k)}) \leq C(k) \] (10)

\[ \sum_{i=1}^{n} I_{ix}^{(k)} \leq I(k); \quad Z^{(l)} = Z^{(l)}[U, S], l = 1, 2, \ldots, 6 \] (11)

\[ a_{ij} \leq U_{ij} \leq b_{ij} \] (12)

Where

- \( A(k) \): oilfield preset or predicted output in \( k \) year
- \( C(k) \): operation cost in \( k \) year
- \( I(k) \): investment in \( k \) year
- \( a_{ij} \): minimum value of influence factor
- \( b_{ij} \): maximum value of influence factor

**Model II Cost minimum**

\[ J_2 = \min \left[ \sum_{i=1}^{n} (C_{iz}^{(k)} + C_{ic}^{(k)}) \right] \] (13)

The constraint conditions are the same of above optimization model with maximum output.

**Model III Profit maximum**

\[ J_3 = \max \left[ P(k) \sum_{i=1}^{n} (X_{iz}^{(k)} + X_{ic}^{(k)} + X_{ix}^{(k)}) - \sum_{i=1}^{n} (C_{iz}^{(k)} + C_{ic}^{(k)}) - \delta \sum_{i=1}^{n} I_{ix}^{(k)} \right] \] (14)

The constraint conditions are the same of above optimization model with maximum output.

Where, \( P(k) \): oil price in \( k \) year; \( \delta \): depreciation and amortization of investment

**Model Multi-objective**

\[ \max J = \{ \lambda_1 J_1 - \lambda_2 J_2 + \lambda_3 J_3 \} \] (15)

\[ \lambda_1 + \lambda_2 + \lambda_3 = 1, 0 \leq \lambda_i \leq 1, i = 1, 2, 3 \]

The constraint conditions are the same of above optimization model with maximum output.

5 **Nonlinear multi-objective algorithm based on PSO**

According to the output programming model’s feature of existing implicit functions, Particle Swarm Optimization algorithm is used for the solving.

5.1 **The basic principle of PSO**

Like some other evolution algorithms, PSO\(^{[2, 7]}\) is based on swarms, and it can move the unit in the swarm to the proper area according to the degree of adaptability to the environment. However, unlike other algorithms which employ arithmetic operators to the unit, PSO sees each unit as a no volume particle in \( D \) dimensions researching space, flying at a certain speed. This speed is dynamically adjusted with its own flying experience and its fellows’ flying experience. So particle \( i \) can be expressed as \( X_i = (x_{i1}, x_{i2}, \ldots, x_{iD}) \), the best positions it has ever passed (having the best adapting value) is marked as \( P_i = (p_{i1}, p_{i2}, \ldots, p_{iD}) \), and it is also called \( P_{i best} \). The index sign for the best positions of all the particles in the swarm is marked as \( g \), or \( P_g \), also called \( g_{best} \). The speed of particle \( i \) is expressed as \( V_i = (v_{i1}, v_{i2}, \ldots, v_{iD}) \). For every generation, the \( d(1 \leq d \leq D) \) dimension is changing with the following equations:
\[ v_{id}(t + 1) = \omega v_{id}(t) + rand(0, c_1)(p_{id}(t) - x_{id}(t)) + rand(0, c_2)(p_{gd}(t) - x_{id}(t)) \]  
(16)
\[ x_{id}(t + 1) = x_{id}(t) + v_{id}(t + 1) \]  
(17)

\( \omega \) is inertia weighting constant and \( c_2 \) are the acceleration constants, \( rand(0, c_1) \) and \( rand(0, c_2) \) are two independent random functions, producing respectively random value in \([0, c_1]\) and \([0, c_2]\).

In order to assure the algorithm is constringent, constringency factor \( K \) is introduced\(^{[10]}\). Then the formula becomes:

\[ v_{id}(t + 1) = K[v_{id}(t) + rand(0, \varphi_1)(p_{id}(t) - x_{id}(t)) + rand(0, \varphi_2)(p_{gd}(t) - x_{id}(t))] \]  
(18)
\[ x_{id}(t + 1) = x_{id}(t) + v_{id}(t + 1) \]  
(19)
\[ K = 2/[2 - \varphi - \sqrt{\varphi^2 - 4\varphi}], \varphi = \varphi_1 + \varphi_2, \varphi > 4 \]  
(20)

After testing different kinds of functions, it has been proved\(^{[10]}\) that after introducing the constringency factor PSO algorithm is superior to the standard PSO algorithm in terms of constringency speed.

5.2 Computation steps

Step 1. Initial. Generate \( m=40 \) particles, the coordinate \( X_i = (x_{i1}, x_{i2}, \cdots, x_{iD}) \) and velocities \( V_i = (v_{i1}, v_{i2}, \cdots, v_{iD}) \) of the initial swarm of particles are randomly generated and ensure \( a_{id} \leq x_{id} \leq b_{id}, 0 \leq v_{id} \leq (b_{id} - a_{id})/15. \) \( D \) equal to the number of decision variables, \( a_{id}, b_{id} \) are the minimum value and maximum value of decision variables. Set the iterative times \( t = 0 \), the maximum iterative times \( T = 50 \).

Step 2. Check the particles is beyond their range, if beyond, this location of the particle will be adjusted on the boundary.

Step 3. Compute the fitness of each particle. Compute the dependent variables (oilfield development index) by decision variables (particles location), if the dependent variables beyond theirs rang, the publish function is added to the objective function when computing the fitness of this particle.

Step 4. Update each particle’s best position \( P_{best} \) and the global best position \( g_{best} \) after comparing its fitness with its former best fitness and the previous global best fitness.

Step 5. Update the position and velocity of each particle’s next generation according to equation (18, 19)

Step 6. Check if reaching the maximum iterative time

Step 7. Output the optimal result including the location coordinate and the solution of output programming.

6 Application

6.1 Data

Oilfield A in china has a serial history data from 1995 to 2004, and there are 6 blocks \( I – IV \) and 7 output stimulation measures. The history data of output is present in Tab. 1, and a segment of influence factors date of development index is present in Tab. 2. The objectives of development programming are set as followings:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>102.62</td>
<td>93.47</td>
<td>81.03</td>
<td>77.20</td>
<td>71.69</td>
<td>73.56</td>
<td>74.51</td>
<td>74.26</td>
<td>72.64</td>
<td>66.91</td>
</tr>
<tr>
<td>2</td>
<td>41.73</td>
<td>39.93</td>
<td>38.85</td>
<td>37.17</td>
<td>37.47</td>
<td>38.03</td>
<td>39.41</td>
<td>39.60</td>
<td>39.28</td>
<td>38.61</td>
</tr>
<tr>
<td>3</td>
<td>194.40</td>
<td>185.35</td>
<td>176.94</td>
<td>174.00</td>
<td>169.17</td>
<td>166.75</td>
<td>174.62</td>
<td>177.87</td>
<td>179.77</td>
<td>176.01</td>
</tr>
<tr>
<td>4</td>
<td>34.37</td>
<td>34.22</td>
<td>34.58</td>
<td>33.97</td>
<td>34.15</td>
<td>35.22</td>
<td>35.19</td>
<td>33.96</td>
<td>33.92</td>
<td>36.18</td>
</tr>
<tr>
<td>6</td>
<td>206.47</td>
<td>203.96</td>
<td>203.61</td>
<td>216.35</td>
<td>229.70</td>
<td>228.67</td>
<td>219.63</td>
<td>217.10</td>
<td>199.58</td>
<td>191.04</td>
</tr>
<tr>
<td>Aggregate</td>
<td>601.62</td>
<td>577.36</td>
<td>557.00</td>
<td>557.27</td>
<td>559.49</td>
<td>561.75</td>
<td>562.91</td>
<td>568.09</td>
<td>556.33</td>
<td>539.88</td>
</tr>
</tbody>
</table>

The oil output is no less than 5 million ton, the cost is not more than 25 billion RMB, and the investment is not more than 8 billion RMB.

MSEM email for contribution: submit@msem.org.uk
Table 2. Segment of the influence factors data of oilfield A

<table>
<thead>
<tr>
<th>Year</th>
<th>UR ((10^4 \text{t}))</th>
<th>OC ((10^4 \text{yuan}))</th>
<th>NWOW (unit)</th>
<th>HR %</th>
<th>RDRR %</th>
<th>NMOW (unit)</th>
<th>NEMOW (unit)</th>
<th>ARRR ((10^4 \text{t}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>2546</td>
<td>147042</td>
<td>1802</td>
<td>68.62</td>
<td>21.17</td>
<td>587</td>
<td>471</td>
<td>5814.73</td>
</tr>
<tr>
<td>1996</td>
<td>26062</td>
<td>148254</td>
<td>1849</td>
<td>71.39</td>
<td>21.29</td>
<td>718</td>
<td>582</td>
<td>5838.39</td>
</tr>
<tr>
<td>1997</td>
<td>26611</td>
<td>150663</td>
<td>2247</td>
<td>72.28</td>
<td>21.43</td>
<td>670</td>
<td>500</td>
<td>5832.74</td>
</tr>
<tr>
<td>1998</td>
<td>27239</td>
<td>158602</td>
<td>2190</td>
<td>72.40</td>
<td>21.57</td>
<td>728</td>
<td>573</td>
<td>5903.10</td>
</tr>
<tr>
<td>1999</td>
<td>27760</td>
<td>179815</td>
<td>2277</td>
<td>72.54</td>
<td>21.71</td>
<td>671</td>
<td>546</td>
<td>5865.88</td>
</tr>
<tr>
<td>2000</td>
<td>28137</td>
<td>184501</td>
<td>2509</td>
<td>73.74</td>
<td>21.97</td>
<td>883</td>
<td>731</td>
<td>5682.86</td>
</tr>
<tr>
<td>2001</td>
<td>28560</td>
<td>189434</td>
<td>2698</td>
<td>76.77</td>
<td>22.2</td>
<td>917</td>
<td>764</td>
<td>5542.53</td>
</tr>
<tr>
<td>2002</td>
<td>29051</td>
<td>196251</td>
<td>2954</td>
<td>78.85</td>
<td>22.36</td>
<td>779</td>
<td>651</td>
<td>5466.57</td>
</tr>
<tr>
<td>2003</td>
<td>29621</td>
<td>189022</td>
<td>3101</td>
<td>80.89</td>
<td>22.51</td>
<td>682</td>
<td>586</td>
<td>5480.62</td>
</tr>
<tr>
<td>2004</td>
<td>30173</td>
<td>208831</td>
<td>3213</td>
<td>81.25</td>
<td>22.68</td>
<td>621</td>
<td>579</td>
<td>5492.47</td>
</tr>
</tbody>
</table>

Note: UR - used reserves OC - Operation cost NWOW - Number of working oil well HR - hydrou rate RDRR - recovery degree of recoverable reserves NMOW - Number of measured oil well NEMOW - Number of effective measured oil well ARRR - accumulated remaining recoverable reserves

6.2 Analysis

The development programming of Oilfield A in 2004 is achieved by using the optimization model with the maximum output. There are \(6 \times (4 + 7 + 1) = 72\) variables in the model which is calculated with PSO algorithm. In the process of computation, the constringency factor \(K\) is supposed to be 0.729, and the acceleration constant is \(\varphi_1 = \varphi_2 = 2.05^{[10]}\).

6.3 Result and discussion

The proceeding curve of fitness of each generation is present in Fig. 7. It is apparent from the Fig. 7 that the PSO algorithm has good astringency and can well calculate the optimization model which includes the implicit functions. The optimization result of controllable influence factors are given in Tab. 3, the optimization result of development indices are given in Tab. 4, and the optimization result in objective hierarchy is given in Tab. 5. From the optimization results, we can see that the results meet the targets of output, cost, and investment.

The result accords with the practical circumstances and it can well meet the profit programming of Oilfield A.

Oilfield A had carried the optimization result above into execution in 2005, and implement result testified that cost per ton in 2005 decreased 5 RMB than it in 2004 which used the traditional top-down optimization method, and finally created aggregate profit more than 50 million RMB.
Table 3. Segment of the influence factors data of oilfield A

<table>
<thead>
<tr>
<th>Block No.</th>
<th>$U_{z1}$ (unit)</th>
<th>$U_{z2}$ (unit)</th>
<th>$U_{z3}$ (day)</th>
<th>$U_{z4}$ ($10^4t$)</th>
<th>$U_{c1}$ (unit)</th>
<th>$U_{c2}$ (unit)</th>
<th>$U_{c3}$ (unit)</th>
<th>$U_{c4}$ (unit)</th>
<th>$U_{c5}$ (unit)</th>
<th>$U_{c7}$ (unit)</th>
<th>$U_{z1}$ (unit)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>286</td>
<td>72</td>
<td>350</td>
<td>24.3</td>
<td>31</td>
<td>17</td>
<td>12</td>
<td>9</td>
<td>0</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>213</td>
<td>51</td>
<td>300</td>
<td>26.7</td>
<td>18</td>
<td>19</td>
<td>9</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>745</td>
<td>136</td>
<td>350</td>
<td>22.1</td>
<td>46</td>
<td>36</td>
<td>0</td>
<td>22</td>
<td>16</td>
<td>2</td>
<td>21</td>
</tr>
<tr>
<td>4</td>
<td>266</td>
<td>63</td>
<td>350</td>
<td>25.4</td>
<td>5</td>
<td>0</td>
<td>7</td>
<td>3</td>
<td>0</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>5</td>
<td>157</td>
<td>38</td>
<td>310</td>
<td>29.5</td>
<td>29</td>
<td>1</td>
<td>0</td>
<td>16</td>
<td>2</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>1082</td>
<td>249</td>
<td>350</td>
<td>23.2</td>
<td>87</td>
<td>28</td>
<td>17</td>
<td>5</td>
<td>21</td>
<td>0</td>
<td>33</td>
</tr>
</tbody>
</table>

Table 4. Optimization outcome of development indices

<table>
<thead>
<tr>
<th>Block No.</th>
<th>$X$ ($10^4 t$)</th>
<th>$X_s$ ($10^4 t$)</th>
<th>$X_c$ ($10^4 t$)</th>
<th>$C_s$ ($10^4 yuan$)</th>
<th>$C_c$ ($10^4 yuan$)</th>
<th>$I_x$ ($10^4 yuan$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>60.97</td>
<td>50.06</td>
<td>5.45</td>
<td>5.46</td>
<td>21721.11</td>
<td>2792.64</td>
</tr>
<tr>
<td>2</td>
<td>39.85</td>
<td>32.14</td>
<td>4.59</td>
<td>3.12</td>
<td>20919.46</td>
<td>2357.97</td>
</tr>
<tr>
<td>3</td>
<td>182.77</td>
<td>149.9</td>
<td>18.53</td>
<td>14.34</td>
<td>60735.79</td>
<td>9604.98</td>
</tr>
<tr>
<td>4</td>
<td>39.45</td>
<td>33.06</td>
<td>4.14</td>
<td>2.25</td>
<td>27242.67</td>
<td>2019.47</td>
</tr>
<tr>
<td>5</td>
<td>30.5</td>
<td>22.83</td>
<td>6.32</td>
<td>1.35</td>
<td>21096.98</td>
<td>3442.69</td>
</tr>
<tr>
<td>6</td>
<td>209.41</td>
<td>181.1</td>
<td>23.36</td>
<td>4.95</td>
<td>65874.25</td>
<td>12155.3</td>
</tr>
<tr>
<td>Aggregate</td>
<td>562.96</td>
<td>469.1</td>
<td>62.39</td>
<td>31.47</td>
<td>217590.3</td>
<td>32373.05</td>
</tr>
</tbody>
</table>

Table 5. Optimization outcome of preset goals

<table>
<thead>
<tr>
<th>Preset Goal</th>
<th>Oil output ($10^4 t$)</th>
<th>Cost ($10^4 yuan$)</th>
<th>Investment ($10^4 yuan$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimization Outcome</td>
<td>562.96</td>
<td>249963.31</td>
<td>≤ 80000</td>
</tr>
</tbody>
</table>

7 Conclusions

This research has found a bottom-up optimization approach that can be used to program the oilfield development. A major contribution is that a class of programming problems in which the marginal effect of subentries are unable to measure or separate can be solved by using the “bottom-up” optimization framework which is embedded with Function Simulations and evolutionary algorithm, for both marginal analysis method and Markowitz portfolio theory are helpless for these problems. In the programming process, the keys are making certain the combination structure of Function Simulations and establishment the quantitative correlational relationships, which direct the precision of the programming model.

A nonlinear programming model with implicit functions was established in this paper and it was solved easily by PSO algorithm, which made easy to realize the programming model in computer and to implement this programming method in real oilfield development.

Acknowledgements

This work is supported by National Center of Technology, Policy and Management at Harbin Institute of Technology, and sponsored by the National Natural Science Foundation of China, Grant No. 70201005, and by the Research Program for Science and Technology of Heilongjiang Province, Grant No. GC04A106, and supported by Program for New Century Excellent Talents in University.

References


MSEM email for contribution: submit@msem.org.uk


