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Economical and balanced production in smart Petroleum Cyber–Physical System

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HIGHLIGHTS

- A production optimization method from fields to markets for Petroleum CPS is proposed.
- The proposed method is a petroleum social workflow aware optimization approach.
- The monetary income is increased up to 311.67% in a year time span in our case study.

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ABSTRACT

In Petroleum Cyber–Physical Social workflows, monetary profit optimization is essential. In this work, a production optimization approach for the Petroleum Cyber–Physical System is proposed which spans the field production to the petroleum social market. Dynamic Programming technique, Linear Programming technique and Stochastic Programming technique are first utilized to improve the monetary profit for a single petroleum company. A market-driven petroleum social workflow aware production optimization technique is then proposed to facilitate profit optimization among multiple petroleum companies. The case study result shows that the monetary income can be increased up to 311.67% in an one year time span.

1. Introduction

Petroleum industry has embraced the emerging Cyber–Physical System (CPS) technologies recently [1,2]. Under the petroleum CPS framework, dynamic exploration of production data and static geological data are used to analyze and manage petroleum production activities. Several CPS related Petroleum research works have been proposed. For example, the work [1] analyzes hidden interwell connectivity on the petroleum field and the work [2] analyzes the potential cyberattack in the petroleum CPS. In the petroleum CPS, real-data of petroleum activities can be obtained by the physical part and by utilizing the cyber part of the system, the production on petroleum field can be managed. The management which impacts the petroleum activities in the next round and subsequently the loop of the petroleum CPS is formed.

Petroleum CPSs can be built for various purposes, among which optimization for petroleum production is regarded as a critical objective in practice. There are previous works considering the problem of production optimization [3,4]. However, they are all focused on the single petroleum field, and they are based on the real-time oil price. But the oil price is determined by the production quantity in the market which is contributed by all petroleum companies. When a large number of petroleum companies increase the production quantity during the time they believe the oil price is relatively high, the real oil price can be decreased since there are excessive production increases. This over suppliance for petroleum over the market can cause a long term continuing decrease of oil price. If all the petroleum companies only working alone without taking other companies into account, the constantly “unwise” strategy can make the whole petroleum suffered downturn. Thus, the production optimization needs to consider the interactions among multiple petroleum companies at the petroleum society level. In the modern petroleum CPS, the petroleum company deploys the daily production optimization and market level suppliance strategy to achieve the maximum profit. For each petroleum company, it periodically monitors the petroleum production related data and optimizes the production procedures accordingly at field level. At the market level, the petroleum company can dynamically adjust the selling strategy to satisfy the current market condition by comprehensively considering the production and the petroleum price. In [5], multiple companies are considered

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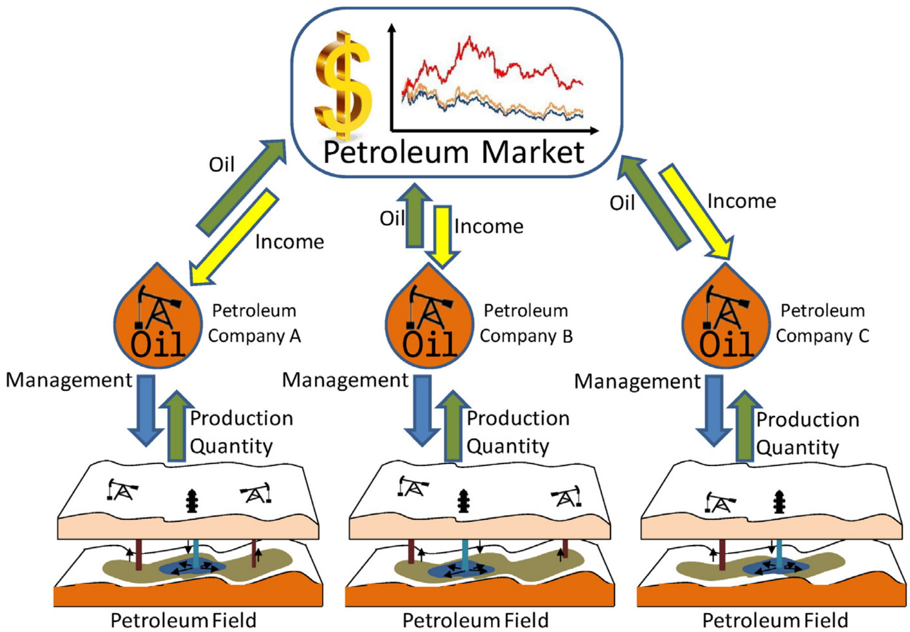

Fig. 1. Hierarchical petroleum production optimization.

using non-cooperative Stackelberg game. In [6] a two-piece von Neumann–Morgenstern utility function based approach is proposed for the Organization of the Petroleum Exporting Countries (OPEC) behavior. In [7], the development of cooperative strategies between countries generating Liquefied Natural Gas (LNG) and members of the Gas Exporting Countries Forum (GECF) are examined by Massol. In [8], a decision-making framework is proposed for the conceptual design and project evaluations in the oil and gas industry. The above works are all focused on the petroleum society level and rarely related to the petroleum field level. The production optimization considering both the petroleum field and the petroleum society is highly necessary. In fact, as shown in Fig. 1 optimization on both the petroleum field and the petroleum society are considered in practice. To tackle this practical scenario, this work develops a hierarchical optimization approach for the petroleum production.

In this paper, a new petroleum production optimization is proposed at the petroleum society level. Utilizing the dynamic programming technique, a single petroleum company based production optimization is first proposed. A game theoretical method is then developed for multiple petroleum companies at the petroleum society level. Contributions of this work are as follows.

- A production optimization approach for the Petroleum Cyber–Physical System is proposed which spans the field production to the petroleum social market.
- Dynamic Programming technique, Linear Programming technique and Stochastic Programming technique are first utilized to improve the monetary profit for a single petroleum company. A market-driven petroleum social workflow aware production optimization technique is then proposed to facilitate profit optimization among multiple petroleum companies.
- The case study result shows that the monetary income can be increased up to 311.67% in an one year time span.

The rest of the paper is organized as follows. Section 2 introduces preliminaries of petroleum optimization for both the single company scenario and the petroleum society level. Section 3 proposes the petroleum profit optimization approach for single petroleum company only. Section 4 proposes the profit optimization method for the petroleum society. Section 5 presents case study results with analysis. A summary of work is given in Section 6.

2. Preliminaries

In this work, the proposed optimization approaches need to iteratively simulate the reservoir under different tentative production scheduling. Thus reservoir modeling is necessary in this work, preliminaries of them are introduced as follows.

Black-oil model which is known as the isothermal oil/water/gas flow model is utilized in this work to simulate the reservoir activities. Three components (oil, water and gas) are modeled together and there are no transfers between the water component and the other two hydrocarbon components. The gas component is the part of the petroleum that turns into gas after differential vaporization and the oil component is the part that remains liquid. Like many other numerical simulations, the targeted reservoir is grided into a set of grid blocks. Each of grid blocks is surrounded by other six blocks. Modeling equations are formulated at each grid block. These equations include principles of mass conservation and Darcy's law. Rather than that, equations of state and constitutive are also needed [9]. Follow these principles, the total liquid volume flow heading into the grid block, shown in Fig. 2 which is for one dimensional flow, have to be equal to the volume of outgoing flow. The black-oil model consists of the oil component, the gas component and the water component. Each of these components can formulate the above principles. Note the gas component includes the solution-gas component which can dissolve in oil and the remaining free-gas component. Detailed modeling formulation can be presented as follows:

For the oil component, there is

$$\sum_{l\in\upsilon_n} T_{o_{l,n}}^{n+1}\left[\left(p_{o_l}^{n+1}-p_{o_n}^{n+1}\right)-\vartheta_{o_{l,n}}^{n}\left(E_l-E_n\right)\right]+\sum_{l\in\varepsilon_n} r_{oc_{l,n}}^{n+1}+r_{oc_n}^{n+1} = \frac{V_{b_n}}{\theta_c\,\Delta t}\left[\left(\frac{\phi S_o}{V_o}\right)_n^{n+1}-\left(\frac{\phi S_o}{V_o}\right)_n^{n}\right]. \qquad (1)$$

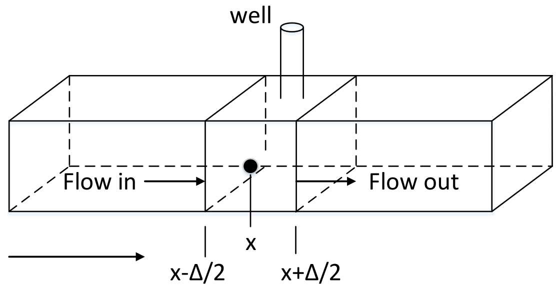

Fig. 2. Grid block in 3D flow.

For the free-gas component, there is

$$\sum_{l\in\upsilon_n} T_{g_{l,n}}^{n+1}\left[\left(p_{g_l}^{n+1}-p_{g_n}^{n+1}\right)-\vartheta_{g_{l,n}}^{n}\left(E_l-E_n\right)\right]+\sum_{l\in\varepsilon_n} r_{fgc_{l,n}}^{n+1}+r_{fgc_n}^{n+1} = \frac{V_{b_n}}{\theta_c\Delta t}\left[\left(\frac{\phi S_g}{V_g}\right)_n^{n+1}-\left(\frac{\phi S_g}{V_g}\right)_n^{n}\right]. \quad (2)$$

For the solution-gas component, there is

$$\sum_{l\in\upsilon_n} (T_oC_s)_{l,n}^{n+1}\left[\left(p_{o_l}^{n+1}-p_{o_n}^{n+1}\right)-\vartheta_{o_{l,n}}^{n}\left(E_l-E_n\right)\right] + \sum_{l\in\varepsilon_n}(C_s r_{oc} p)_{l,n}^{n+1}+(R_s r_{oc})_n^{n+1} = \frac{V_{b_n}}{\theta_c\Delta t}\left[\left(\frac{\phi C_s S_o}{V_o}\right)_n^{n+1}-\left(\frac{\phi C_s S_o}{V_o}\right)_n^{n}\right]. \quad (3)$$

For the water component, there is

$$\sum_{l\in\upsilon_n} T_{w_{l,n}}^{n+1}\left[\left(p_{w_l}^{n+1}-p_{w_n}^{n+1}\right)-\vartheta_{w_{l,n}}^{n}\left(E_l-E_n\right)\right]+\sum_{l\in\varepsilon_n} r_{wc_{l,n}}^{n+1}+r_{wc_n}^{n+1} = \frac{V_{b_n}}{\theta_c\Delta t}\left[\left(\frac{\phi S_w}{V_w}\right)_n^{n+1}-\left(\frac{\phi S_w}{V_w}\right)_n^{n}\right]. \quad (4)$$

υ_n is the set of existing grid blocks (that are neighbors to grid block n and ε_n is all reservoir boundaries which share with grid block n. E_l and E_n represent the elevation of grid block l and n. θ_c is the volume conversion factor and ϑ_o is the gravity of oil-phase at reservoir conditions. r_{fgc}, r_{oc} and r_{wc} are production rate of free-gas, oil-phase and water-phase component under standard conditions. Δt is the time step in the simulation. p is the pressure, S is the saturation of each phase and C_s is the solution GOR. V_o, V_w, and V_g are the oil, water and gas formation volume factor respectively. V_{b_n} represents bulk volume of block n.

The flow of oil, water and gas is coexist, such that:

$$S_g = S_{fg}+S_{sg}, S_g = 1-S_o-S_w, \quad (5)$$

where S_g, S_o and S_w stand for the saturation of oil phase, water phase and gas phase and S_{fg} and S_{sg} represent the saturation of free-gas phase and solution-gas phase respectively.

There are also capillary pressure constraints in the simulation, which is,

$$p_w = p_o - P_{owc}\left(S_w\right), \quad (6)$$

$$p_g = p_o + P_{goc}\left(S_g\right), \quad (7)$$

where p_o, p_g, p_w represent the pressure of oil phrase, gas phrase and water phrase respectively. P_{goc} is gas/oil capillary pressure and P_{owc} is oil/water capillary pressure.

Bring $p_g - S_g$ formulation into the gas/water flow model, and there are,

$$S_w = 1 - S_g \quad (8)$$

$$p_w = p_g - P_{gwc}\left(S_g\right). \quad (9)$$

where P_{gwc} is the gas/water capillary pressure.

By solving the above equation arrays, the flow activities of the reservoir can be calculated and thus the reservoir can be simulated. For more details of the reservoir simulation model, please refer to the literature [10].

3. Petroleum production optimization for single company scenario

In this work, the ultimate target is to optimize the monetary benefits at the petroleum society level. The optimization method can be treated as a two-step approach. The first step is to maximize the monetary profit at one company site, and the second step is to maximize the monetary income for each company at petroleum social level. Since, every petroleum company operates production procedures on the petroleum field. Thus, production optimization on the petroleum field is focused for single company scenario.

In this section, the quantity of the production on the petroleum field is first proposed to provide more opportunities for the optimization at market level. At the market level, a price model is introduced to compute monetary profits for the petroleum company. Since, there are always variations in reality for any price prediction model. A Linear Programming (LP) technique based deterministic optimization method is proposed to maximize the profit and, based on it, a stochastic programming optimization method is proposed to tackle the model variation.

3.1. On field production quantity optimization

For a G&O field, there are a series of adjustable production activities in the production. For example, as shown in Fig. 3, the water injection at the injection well can help to push oil out of the reservoir through production wells. This injection activity can be processed by the petroleum control unit which are separators and chokes. Note that, the injection is one of production activities which also includes tuning the limitations of well yield or well bottom pressure, tuning the pumping strategy on production well and etc. In this paper, the strategy of injection well is mainly taken into consideration. Scheduling of injection well is constrained with the earliest injection time, the latest injection time and the limitation of injection volume per unit time. For example, an injection well cannot inject more than 1 ton water in 15 days and can scheduled anytime from between 1994 and 2000. In this example, the earliest injection time is in January, 1st, 1994, the latest injection time is in December, 31st, 2000 and the limitation of injection volume in every 15 days is 1 ton.

In this work, the scheduling time horizon is divided into T discrete intervals. To make the production scheduling over a series of different injection strategies, the reservoir modeling technique is utilized to simulate the well producing process and compute the total oil yield. Let the array of $\Phi_m = \{a_{1m}, a_{2m}, a_{3m}, \ldots, a_{nm}\}$ represents the mth partial solution, a_{nm} represents the scheduling action in the nth time interval and $\Gamma()$ represents the function of reservoir model. Daily average production of crude oil in the current time interval can be calculated by the reservoir model. In

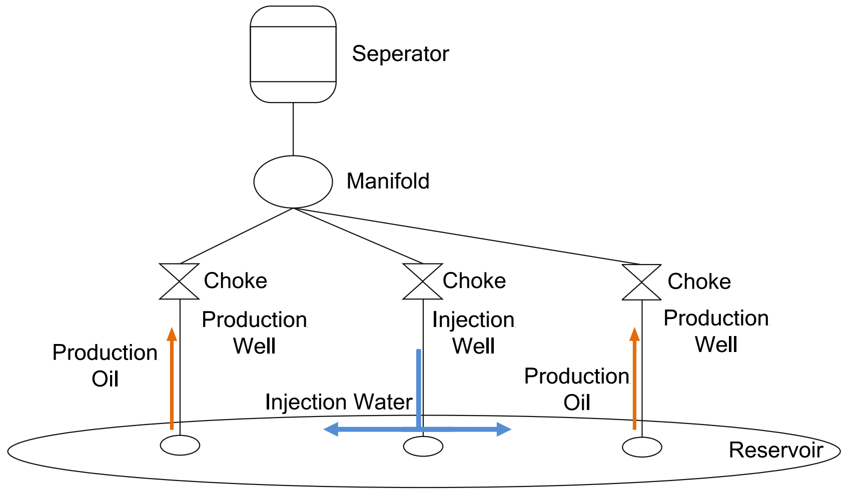

Fig. 3. On field management for petroleum production.

this way, the problem formulation for one petroleum company can be described as follows: (10).

$$\begin{aligned} & max: \ \{P_1, P_2, P_3, \ldots\} \\ & S.T. P_m = \sum_j \frac{T_{sum}}{T} \Gamma(\Phi_m)_j, \ for\ j = 1\ to\ T \\ & \qquad \Gamma(\Phi_m)_j = f(a_{jm}), \ for\ j = 1\ to\ T \\ & \qquad \Phi_m = \{a_{1m}, a_{2m}, a_{3m}, \ldots, a_{Tm}\} \end{aligned} \tag{10}$$

where T_{sum} is the total injectable time. P_m is the oil quantity under the partial solution Φ. Through $\Gamma(\Phi)$. Daily production can be computed by the function $f(a_{jm})$.

To tackle the above problem, a dynamic programming technique based algorithm has been proposed as shown in Algorithm 1. Inputs of the algorithm are the earliest injectable time t_s, the latest injectable time t_e, the threshold of stop criteria of ΔR, injection constraints V_m, the total number of injection wells N_w and reservoir model $\Gamma(a)$. Outputs of the proposed algorithm are the simulated maximum production amount P_{om} and its corresponding production activities set Φ. In the proposed algorithm, the variables of Ω, P, Φ, R_m, T_m and n are initialized. Where the set Ω is used to store the best production activities, P is used to store the production result of the partial production activities, the array Φ is used to store the current production activities, R_m and T_m represent the current best improving ratio compares to no water inject solution and its injection time interval respectively.

First, under the condition of no water being injected, the production quantity can be calculated by the reservoir model in step 2. From step 3 to step 22, the algorithm keeps adding injection water times until the improving value of increasing ratio $R_m - R_{m-1}$ being less than the stop criteria threshold ΔR. From step 4 to step 19, the algorithm would examine the solution profit of injecting water in different time intervals. The algorithm evaluates the solution profit of injecting water in different wells from step 5 to step 17. Before to start "injecting water", whether the time interval t has already been a "injection day" need to be checked from step 6 to step 8. If it is not a "injection day", in step 9, a new partial solution a_{tm} is to be added into the set $\Phi[n]$ which stores the current scheduling solution. Calculate the current production P after adding the solution a_{tm} by the reservoir model $\Gamma(a)$ in step 10. In step 11, the current improving ratio R_n is computed. From step 12 to step 15, the inferior solution can be pruned by comparing to the best solution from current state, and the scheduling solution with biggest production of current loop is selected to the set Ω. Thus, entire scheduling solutions are stored in the set Φ at the end of this algorithm.

Algorithm 1 The dynamic programming based production optimization algorithm for a single company.

Input: t_s, t_e, ΔR, V_m, $\Gamma(a)$, N_w.
1: initiate Ω, P, array Φ, $R_m \to 0$, $T_m \to 0$;
2: $P_0 \to \sum_{j=0}^{T} \frac{T_{sum}}{T} \Gamma(a_{j0})$;
3: **while** $R_{m-1} - R_{m-2} < \Delta R$ **do**
4: **for** each $t \in [t_s, t_e]$ **do**
5: **for** each $w \in [1, N_w]$ **do**
6: **if** $t \in \Omega$ **then**
7: continue;
8: **end if**
9: $\Phi[n] \to a_{tm}$;
10: $P \to \Gamma(\Phi[n])$;
11: $R_n \to \frac{P - P_0}{P_0}$;
12: **if** $R_m < R_n$ **then**
13: $R_m \to P$;
14: $T_m \to t$;
15: **end if**
16: $n \to n + 1$
17: **end for**
18: $[T_m, \phi]$ add Ω
19: **end for**
20: $\Phi \to 0$, $R_m \to 0$, $T_m \to 0$, $n \to 0$, $m \to m + 1$;
21: Φ add Ω
22: **end while**
Output: P_{om} and Φ.

3.2. Production data based pricing modeling

The quantity of oil sale is an essential and adjustable factor that can impact the crude oil price. Organization of Petroleum Exporting Countries (OPEC), established in 1960s, gradually undertake the task of adjusting the global oil prices after 1970s. According to data statistics of OPEC, only in 1974, 1980 and 1999, the increasing of oil quantity leads to a decreasing of oil price from 1971 to 1999 [11]. By means of multiple regression analysis of the price and quantity data, the functional relationship among price and quantity is established as shown in Eq. (11).

$$\begin{aligned} & S_t = \zeta + \sum_i \alpha_i P_i \\ & 1.7 < S_t < 35.52, \forall i \in [1, t] \\ & \alpha_0 < \alpha_1 < \cdots < \alpha_t \end{aligned} \tag{11}$$

where P_t and S_t represent the oil quantity and price at time t respectively. α_i is the weight value of the oil quantity at time i and weights are increasing progressively while approaching to the time t. ζ is a constant which is utilized to balance the effect of other inconsiderable factors to the oil price. According to the historical data between year 1971 and 1999, the oil price S_t is set to be less than the maximum oil price \$35.52 per barrel and greater than minimum oil price \$1.7 per barrel in that period. To build a regression model for the oil price, the least square approach are utilized in this work with parameters of ζ and α. Note that, $\beta, b_1, b_2, \dots, b_t$ are assumed to be least-square estimation of $\zeta, \alpha_1, \alpha_2, \dots, \alpha_t$ and Eq. (11) can be reformed as:

$$S_t = \beta + \sum_i b_i P_i. \tag{12}$$

For each group of P, a certain value of S_t is computed. If S_t is close to the real price, the regression model has the better ability to simulate the real problem. Assume that $\hat{S}_t$ represents the real oil price at time t. The sum of bias squares is

$$\begin{aligned} Q(\beta, b_1, b_2, \dots, b_t) &= \sum_j \left(S_{tj} - \hat{S}_{tj}\right)^2 \\ &= \sum_j \left(S_{tj} - \beta - \left(\sum_i b_i P_{ij}\right)\right)^2 . \end{aligned} \tag{13}$$

For the limit theory in differential calculus, unknown parameters $\zeta, \alpha_1, \alpha_2, \dots, \alpha_t$ are the solution of following equations

$$\begin{cases} \dfrac{\partial Q}{\partial \beta} = -2\sum_j \left(S_{tj} - \hat{S}_{tj}\right)^2 = 0 \\ \dfrac{\partial Q}{\partial b_k} = -2\sum_j \left(S_{tj} - \hat{S}_{tj}\right)^2 Pj = 0.(j = 1, 2, \dots, T) \end{cases} \tag{14}$$

According to Eq. (11), calculated by the OPEC statistics, α_t is positive, for $\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_{t-1}$, positive correlations exist between oil price and current production, and negative correlations with previous oil productions. The high oil production leads to the price deflation in the following time, but the high oil price can encourage oil companies to increasing the oil production.

Note that, this price model has variations in practice. There are other impact factors, such as politics, market demand, social development etc., which can effect oil price as well. Therefore, in this paper, this price model is first used to solve a deterministic optimization problem. After that, a stochastic programming technique is used to tackle the variations of the price model.

3.3. Deterministic programming based optimization

Assuming that, there is no variation with the price model. To maximize the monetary profit oil price Linear Programming (LP) technique is utilized for a deterministic solution. Suppose that C_i and a_i represent the oil price and oil sale quantity at time interval i, C_{il} and C_{ih} are the lowest and highest current oil price while considering the effect of other factors. The optimization target is illustrated as Eq. (15).

$$\begin{aligned} maximize: \sum_i^n C_i a_i - C_r R_i \\ S.T.\ C_{il} \le C_i \le C_{ih} \\ a_{il} \le a_i \le a_{ih} \\ a_{ih} = P_i + R_{i-1} \\ 0 \le R_i \le R_h, \\ R_i = R_{i-1} + P_i - a_i \end{aligned} \tag{15}$$

where a_{il} and a_{ih} are minimum and maximum sale amount at time interval i. C_r is the oil storage cost and R_i is the reserved oil volume at time interval i. R_h is the maximum amount of oil reserved. P_i represents the oil quantity at time interval i. Maximum sale amount a_{il} at time interval i is the oil quantity at time interval i and reserved oil volume at time interval $i-1$. The reserved oil volume at time interval i can be computed by the current sales volume, current oil production and last reserved oil volume. For each time interval, the crude oil can be either sold or store for the future sale.

3.4. Stochastic programming based optimization

In practice, the crude oil price is not only correlated to the total quantity of production, it also has variations which can be caused by other issues, such as political situations. To tackle this variation issue, this paper proposes a stochastic programming technique based approach for the monetary profit optimization.

Suppose that, crude oil price is various in a range of $[C_l, C_h]$, then how to determine what is the value of C_i within the range. Stochastic programming technique with Monte Carlo simulation is utilized. A yield value τ is introduced to determine the value of C_i. Motivated by [12], this paper defines that:

$$C_i = \tau_i C_{il} + (1 - \tau_i) C_{ih}, \ \tau \in [0, 1] \tag{16}$$

where τ_i is the yield value at the time interval i.

The algorithmic flow for scheduling optimization is shown in Fig. 4. First of all, the oil price range at every time interval, maximum amount of reserved oil, reserve cost and minimum turnover at one time interval require to be set in advance. Then, yield value τ, which is in the range of 0 to 1, can be divided into t times. For each yield value τ_i, based on the restrictions (15), the best marketing strategy can be computed utilizing linear programming algorithm. By means of Monte Carlo method, a large number of oil price is generated in the price range that are set at first. Compute total profits for generated partial oil prices under current best marketing strategy. To eliminate the influence of extreme value, the best price situation and worst price situation are pruned. The average total profit is calculated by rest of situation. Compare the average profit among different marketing strategy in different yield value τ_i. Select marketing strategy with maximum average value as a round result of the stochastic programming based optimization process.

4. Market-driven petroleum society aware production optimization

Assuming that every single company utilizing the dynamic programming optimization algorithm as illustrated in Section 3, companies are about to sell as much oil as they can to make maximum profit at the peak price. As a result, the crude oil price can rapidly decrease when the daily sold volume is significant. Thus, oil companies are required to collaborate and compete to make maximum profit over time.

Assuming that every single company utilizes the dynamic programming optimization algorithm as illustrated in Section 3, companies are supposed to sell crude oil as much as they can at the peak price. But according to the real pricing model, a negative correlation exists between oil price and oil quantity. Oil price can be reduced when the daily sold quantity is increased. At petroleum society level, companies are required to collaborate and compete to make maximum profit over time. In this work a multi-company driven price variation aware approach is proposed for production optimization at the petroleum society level.

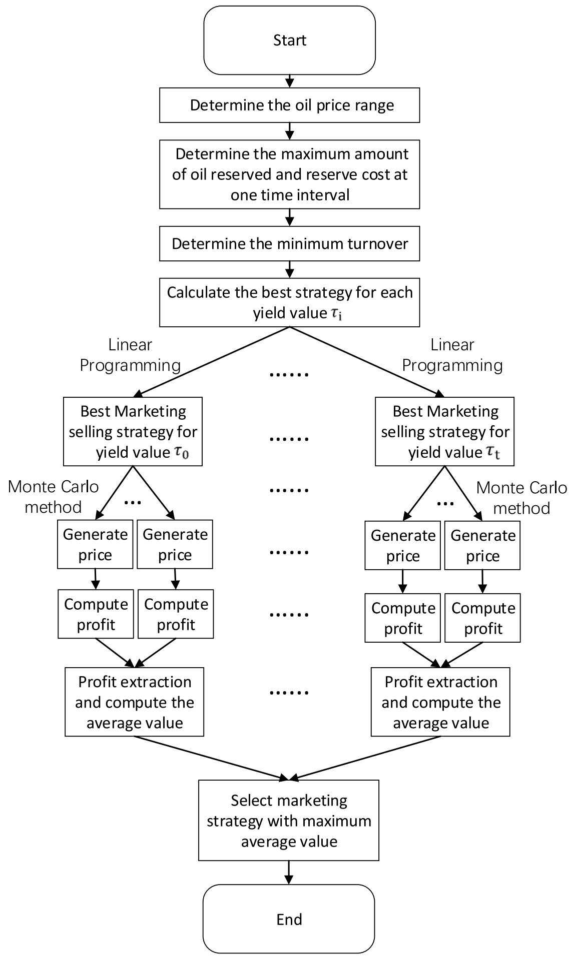

Fig. 4. The process of stochastic programming based optimization.

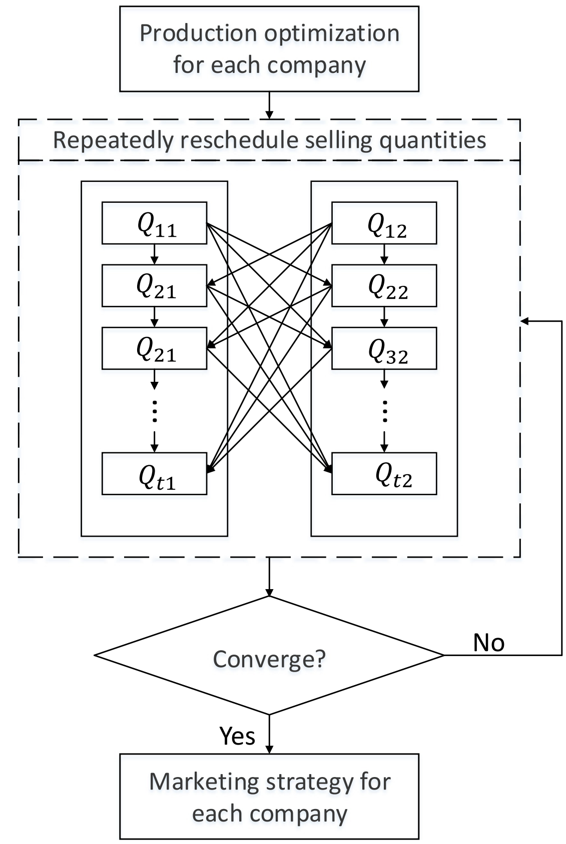

Fig. 5. The process of multi-company interacted production optimization.

In this approach, every company can select one marketing strategy from all possible solutions to maximize its profit. When no player can increase its profit without changing the operation of others, a convergence is met. It is a solution concept of a non-cooperative game involving two or more players in which each player is assumed to know the equilibrium strategies of the other players, and no player has anything to gain by changing only his or her own strategy [13].

For the game theoretic algorithm, after each company optimize the production to gain the maximum oil quantity at one time interval, they drawn up their marketing strategies at current time interval without considering other oil companies. Then, at the next time interval, they re-schedule second time interval strategy according to the last time interval the oil production quantities of other companies. For example, at the time interval t, the company i obtain history sale quantities $\{Q_{11}, Q_{12}, Q_{13}, \dots, Q_{1n}\}$, $\{Q_{21}, Q_{22}, \dots, Q_{2n}\}$, ..., $\{Q_{t1}, Q_{t2}, \dots, Q_{tn}\}$ and total quantities of each time interval is $\sum_i^n Q_{1i}$, $\sum_i^n Q_{2i}$, ..., $\sum_i^n Q_{ni}$. Given these total sale quantities of all companies, oil price in time interval t can be estimated by company i and company i will re-schedule the sale quantity. Other companies similar to company i. After all the time interval are scheduled, calculate total profit of each company. Repeat these process until the equilibrium is achieved. In other words, this process terminates when no company can increase its total profit of sale oil any more by changing sale solution. The two companies participating game theoretic algorithmic flow is as Fig. 5, where Q_{ij} is the sale quantity Q of company j at time interval i, t is the number of time interval and n is the number of company.

5. Case study

The reservoir modeling for production simulation is based on the $PUNQ - S3$ case which has been taken from a reservoir engineering study on a real field performed Elf Exploration Production and the field contains 6 wells located around the Gas Oil contact [14]. Porosity and permeability fields are generated utilizing a Gaussian Random Field based geostatistical model. Pressure, volume and temperature (PVT), aquifer data from the real situation and with power law relative permeability functions are required to complete this model. In addition, Gaussian noise, which is able to correlate in time to mimic the more systematic character of errors for production data, is added into the model.

For the single company production optimization experiment, we optimize the production process through inject the water into the well. Due to the strong aquifer of field, more than one injection well will cut down production quantities. We choose one well $PRO - 15$ as a injection well and five well $PRO - 1$, $PRO - 4$, $PRO - 5$, $PRO - 11$, $PRO - 12$ as production wells. The total time is from January 1st 1967 to July 31st 1983. We assume that inject water at the 1st day and 10th day of month, which means we separate the total time into 398 time intervals. In each intervals, whether inject water are required to decided. If need to inject, we inject maximum volume of water that can be inject into the well.

For the production optimization of multiple companies, we firstly take two companies into consideration. And for the price model, because merely no effect to current oil price for selling oil quantities before two times, we assumed that in equation 11, if i is less than $t - 2$, α_i equals to 0. After the regression analysis, the equation 11 can be transformed into follows.

$$S_t = 1099.4 - 4.7747P_t - 1.5195P_{t-1} - 6.8168P_{t-2}, \quad (17)$$

Table 1
The optimization result of single company.

Time	0	1	2	3	4	5
Date	0	1967.4.1.	1967.4.10.	1967.6.1.	1967.5.10.	1967.8.10.
$Q(m^3)$	5 383 918	5 421 630	5 425 936	5 426 470	5 426 980	5 427 459
Rate	0.0000%	0.7004%	0.7804%	0.7904%	0.7998%	0.8087%
Time	6	7	8	9	10	11
Date	1967.7.10.	1983.7.10.	1967.9.10.	1967.10.10.	1967.6.10.	1973.10.1.
$Q(m^3)$	5 427 875	5 428 260	5 428 610	5 428 922	5 429 210	5 429 732
Rate	0.8164%	0.8236%	0.8301%	0.8359%	0.8429%	0.8509%
Time	12	13	14	15	16	17
Date	1968.10.10.	1967.7.1.	1967.5.1.	1973.1.10.	1967.8.1.	1968.2.1.
$Q(m^3)$	5 429 980	5 430 222	5 430 474	5 430 718	5 430 950	5 431 197
Rate	0.8554%	0.8600%	0.8647%	0.8693%	0.8736%	0.8782%
Time	18	19	20	21	22	23
Date	1970.11.10.	1968.7.10.	1968.6.10.	1971.11.10.	1968.12.10.	1968.11.10.
$Q(m^3)$	5 431 428	5 431 652	5 431 872	5 432 088	5 432 302	5 432 508
Rate	0.8824%	0.8866%	0.8907%	0.8987%	0.8987%	0.9025%

where parameters are calculated utilizing the OPEC statistic from 1971 to 1999. In the experiment, a time interval is a month and the oil price range is from \$5 per barrel to \$120 per barrel. The reserve cost per time interval is \$0.3 per barrel. The maximum amount of reserved oil is 400 barrels. The minimum and maximum turnover at one time interval is 25 and 550 barrels.

Results of optimizing production quantity for single company are shown in Table 1. *Time* represents the injection time. *Date* represents one injection day that can maximize the oil production based on the last time solution. Q represents the total oil quantity. *Rate* represents the total improving rate comparing to the no injection solution. Note that for each time t, the scheduling solution is adding all the current best solution together $\{date_1, date_2, \ldots, date_n\}$. For example, two times injections, apart from injecting water at April 10th 1967, also need to inject at April 1st 1967. According to Table 1, adding water first 12 times brought a rapidly increase to the total production and its increasing rate is 0.8164%. Then, from 13rd to 23rd time, the total production increases slowing and at 23rd time, the rate reaches 0.9025%.

In order to prove the effective of the proposed linear programming based marketing strategy for single company in stochastic programming based optimization, there are two comparison strategies examined in the case study. The first strategy, named conventional strategy, sells all petroleum production in each time interval. The second strategy, named improved conventional strategy, on the basis of the conventional strategy principle, considers special affairs which could influence the oil demands. For example, people tend to take vocation in Christmas which would enhance the market oil demands and it is a wise choice to increase the oil suppliance. Note that crude oil prices utilized in this part is monthly oil prices in 2016 [15].

Results of monetary income for the company have been shown in Fig. 6. Total profits of all the company utilizing the linear programming based marketing strategy and conventional strategy are steadily increasing in a year. In the first month, the profit of linear programming based strategy is only 699.5 dollars while conventional strategy and improved conventional strategy is 5139.4 dollars. The linear programming based marketing strategy reserves the petroleum when the price is low and makes the best profit when the price is high. After 12 months, the profit of linear programming based strategy is up to 97536.4 dollars. For conventional strategy and improved conventional strategy, the profit is about 88662 dollars and 89139 dollars less than linear programming based strategy. The improvement of linear programming based marketing strategy is $10.01\% = \frac{97536.4-88662}{88662} \times 100\%$ and $9.42\% = \frac{97536.4-89139}{89139} * 100\%$ comparing to the conventional strategy and the improved conventional strategy.

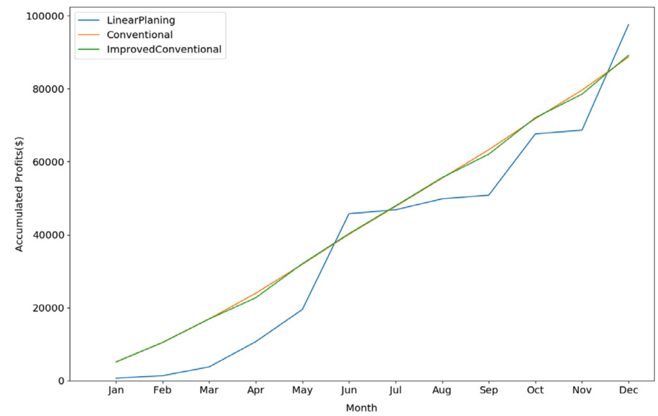

Fig. 6. Accumulative profits of different marketing strategy for in a year.

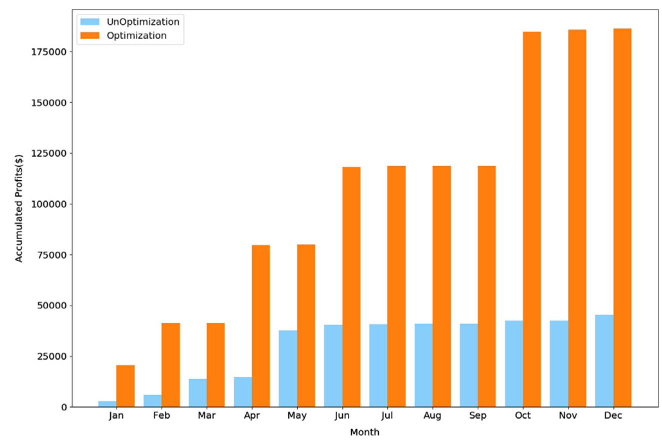

Fig. 7. The result of different petroleum society level marketing strategy optimization.

Petroleum society level results are illustrated in Fig. 7. "Unoptimization" bars in the graph represent utilizing the linear programming based marketing strategy to sell petroleum with multiple companies in society. "Optimization" bars represent utilizing the linear programming based marketing strategy iteratively to compete other companies until all companies making the best full-year profit. The figure shows that there is a rapid increase in total profit with years. Comparing to the un-optimized method, the total profit of the linear programming based game theory marketing strategy is increasing more rapidly. In 12 months, the total profit of optimization method can reach 45307.1 million dollars while un-optimization profit only can reach 186514.6 dollars. From the result we can conclude that the linear programming based game theory marketing strategy increases about $311.67\% = \frac{186514.6-45307.1}{45307.1} \times 100\%$ profit than un-optimized method in a year.

6. Conclusion

In this work a monetary profit optimization flow has been proposed for Petroleum Cyber–Physical Systems. The proposed method includes optimization for both single company scenario and multiple company scenario, in which optimization for multiple company scenarios is based on the single company one. The proposed method first optimizes the on field production quantity by the dynamic programming technique. Based on it, the monetary profit for a single company is optimized by using the Linear Programming technique, and the price prediction variation is considered and solved by stochastic programming technique. After that, the optimization is built for the petroleum society level, and the case study result shows that the monetary income can be increased up to 311.67% in an one year time span.

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