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Research Article

An Improved Fair Allocation Based on Contribution Rate and Its Application

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Oil production task allocation (OPTA) is affected by various factors, and each one has a different impact on oil production. Therefore, the fair distribution of production task to each production branch is really a hard work for an oil company, so a fair allocation based on contribution rate (ABCR) has been proposed to solve this problem in this paper. The algorithm of ABCR, unlike other existing algorithms, takes into account the differences of members' contribution (DMC), which can be expressed by member contribution rate (MCR) based on the certainty and uncertainty factors. Two steps are implemented to gain the differences of members' contribution. First, we use Principal Component Analysis (PCA) to reduce factors for certain factor and construct a new factor with Analytic Hierarchy Process (AHP) for uncertain factor. Then, the MCR is evaluated by AHP. Based on member contribution rate, member goal, and alliance target, a fair allocation can be obtained by ABCR. Finally, we propose an evaluation criterion for allocation. Case study shows that the resource allocation results of ABCR not only are more reasonable than those of the other methods but also can prevent unfair allocation and enhance the production environment, thereby improving the enthusiasm for production.

1. Introduction

1.1. Background and Related Work. Traditionally, alliance activities can play a constructive role to each member and maximize the benefits of alliance. As benefits increase, some questions follow. For example, the fair allocation of benefits will become more difficult. No wondering that each member will try to grab as more benefits as it can. Therefore, it is a great challenge to find an allocation algorithm for members in alliance benefits and ensure that each member is profitable. Fair allocation algorithm seems to be a satisfactory solution. Fairness has been taken into account as one of the important additional criteria in many application domains, such as resource allocation [1], big data processing [2–4], and industrial procurement [5, 6], but how to get a fair allocation has been puzzling researchers for many years.

In traditional fair allocation algorithms, member goal and alliance target are commonly the two effect factors. However, recently researchers have found that the two effect factors are not the only effect factors in a fair task allocation [7–11]. Although there is no common definition for the term, there are three fairness criteria that are generally used in the literature: proportional allocation, Shapley value, and Nash bargaining solution.

Some simple solutions of allocation usually allocate the benefit by proportional allocation. The proportional allocation is generally the most intuitive procedure. In some cases, the accuracy of the assignment results is not very strict; this method is still often used in actual programs. However, this issue of fair allocation is not comprehensive.

Shapley value [12, 13] is a useful and theoretical allocation algorithm. It is fair and reasonable and has an axiomatic basis that uses the linearity, dummy, symmetry, and validity axiom to allocate the interests of alliance members. However, it is hard to confirm benefits of all cooperative members, that is, to define characteristic functions of all subsets (total number is $2n - 1$) in $I = \{1, 2, \cdots, n\}$. Therefore, this method is less applied in practice in actual programs. Despite this, the

research of this field has been further developed recently [14–17]. Nash bargaining solution (NBS) is another famous fair allocation method [18]. The calculation of this method is simple and easy to grasp. However, it is not fit to apply to members with different strength. There is also a minimum distance solution and a satisfactory solution similar to this approach [19, 20].

1.2. Motivation. Many challenges exist in our studying of oil production task allocation algorithm.

(1) The effect factors of the next year's oil production task have significant differences from those of the last year. The change of each factor is unpredictable. And these factors can be divided into certain factors and uncertain factors.

(2) To the best of our knowledge, the existing fair allocation algorithm cannot be directly applied to address our problem because the existing allocations algorithms ignore the dummy factors unfair allocation in alliance activities [21]. For example, a modern oil company usually has many oilfield branches, and different branches often have different geographical locations, staff structures, production scales, and management levels. In order to maximize the overall benefits of enterprises, the tasks of each oilfield branch will not be divided into fixed proportions. Therefore, the investments and benefits of oilfield branches in the alliance are not necessarily proportional; sometimes there even exist big differences.

(3) It is very important to achieve fairness allocation in the oil production task collocation, but the process of distribution is difficult. To realize fairness allocation, member contribution rate (MCR) is considered in our algorithm.

(4) The MCR can be generated from some certain factors and some uncertain factors of the oil company. This poses a difficulty because obtaining the information is expensive. Therefore, an effective circumvent way to solve this difficulty is to create some combination factors, which include some selected certain factors and a constructed uncertain factor, to evaluate the member contribution rate in task allocation.

In our oil production task allocation program, we assume that we know the previous production task of each branch and decide to cooperate to produce in next year. According to the production contribution rates of oilfield branches, respective production capacity, and the production tasks of the oilfield branch, to allocate the oil production task fairly to each oilfield branch is possible.

To solve this problem, we propose an allocation algorithm based on member contribution rate, which can rationally allocate tasks or benefits of members in alliance. This strategy not only gave an evaluation method for the differences of members' contribution (DMC) in alliance activities, but also designed an allocation algorithm called fair allocation based on contribution rate (ABCR). We express the DMC by member contribution rate (MCR), which is used to express the members' difference in alliance based on the certainty and uncertainty factors of the construction. There are two steps in implementing the differences of members' contribution. First, we use Principal Component Analysis (PCA) [22] to reduce factors for certain factor and construct a new factor with Analytic Hierarchy Process (AHP) [23] for uncertain factor. Then, the MCR is evaluated by AHP. Based on member weight rate, member goal, and alliance target, a fair allocation can be obtained by ABCR.

1.3. Contribution. The contribution of this paper can be summarized as below.

(1) A fair allocation algorithm based on member contribute rate was proposed in this paper. This algorithm not only can achieve fairness in the oil production task allocation easily, but also can be applied to other similar projects.

(2) Member contribution rate, which expresses the contribution rate of each member in alliance activities, is defined. Unlike other approaches, this definition quantifies each member's contribution in affiliate activity.

(3) A fairness criterion was designed firstly. It can solve the problem that it is not clear how to evaluate and compare these allocation algorithms implemented.

The rest of this paper is organized as follows. We proposed an improved fair allocation based on member's contribution rate in Section 2, followed by the algorithm of ABCR in Section 3. In Section 4, a fair allocation criterion was introduced. In Section 5, a case study shows its fairness. Finally, conclusions and some interesting directions of future work are provided in Section 6.

2. An Improved Fair Allocation Based on Member Contribution Rate

For N-person cooperative allocation, proportional allocation only requires the past benefit (threat points) of each member and the cooperative benefit of the alliance. Although this solution is simple, there is irrationality in implementing fair allocation. And Nash bargaining solution needs to consider the role of subcoalitions $S \subseteq N$ of members beside threat points and alliance target. However, this is unrealistic in a practical engineering problem of allocation cooperation.

For example, in oil production task allocation, we usually know the production capacity of each oilfield branch, as well as its technical and management information in task allocation. That is to say, there is no need or it is impossible to know the production capacities of the different combinations of each oilfield branch. In other words, it is not necessary to consider the subcoalition; we only consider the "all oilfield branches coalition" in our task allocation. Thus, to achieve the fair allocation of oil production tasks, we made the following assumptions.

2.1. Assumption

Assumption 1. Our task allocation argues that the contribution of different members in the alliance activities is inconsistent.

Assumption 2. Our task allocation ignores the role of subcoalitions of $S \subseteq N$ players.

2.2. Member Contribution Rate. Member contribution rate (MCR) that can be calculated by some certainty and uncertainty effect factors of oil production is used to determine the

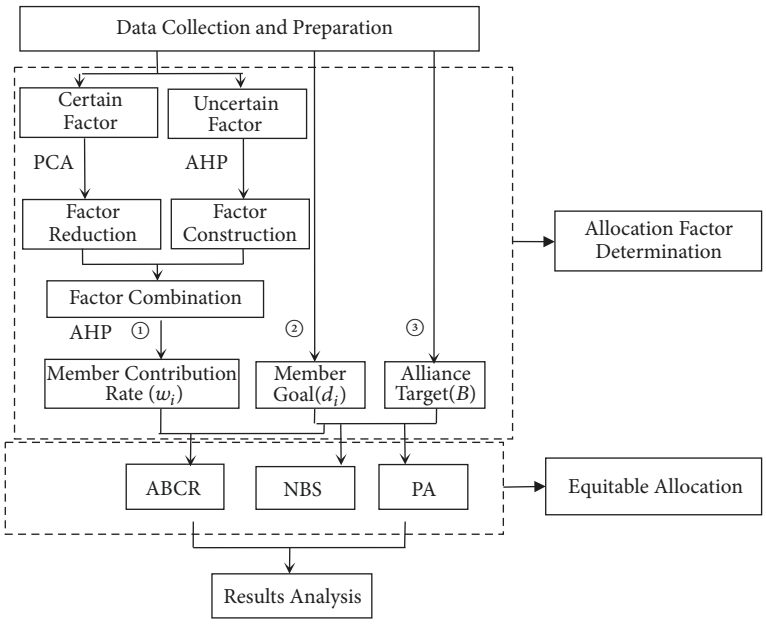

Figure 1: Framework of ABCR.

differences of member contribution (DMC). In the alliance activity there are two steps to obtain the MCR. First, we use PCA [22] to reduce factors for certain effect factors and construct a new factor with AHP [23] for uncertain effect factors. Then, the MCR is calculated by the reduced factors and a constructed factor through AHP.

2.3. The Framework of ABCR. The algorithm of ABCR is planned to be composed of three parts: member contribution rate, member goal, and alliance target. The framework of ABCR was designed as in Figure 1. There are 4 steps in this framework: (1) data collection and preparation, (2) allocation factor determination, (3) fair allocation, and (4) results analysis.

After data collection and preparation, the next step is to determine the allocation factors, which includes three parts: member goal, alliance target, and member contribution rate. NBS and PA mainly rely on member goal and alliance target, while in ABCR member contribution rate is also an indispensable condition.

In step 3, while member goal (d_i) and alliance target (B) can be obtained directly from the collected data, member contribution rate (ϖ_i) needs to be calculated by a program. In this program, information about certain and uncertain effect factors can be obtained from step 1. From certain effect factors, we use PCA for factor reduction. From uncertain effect factors, we use AHP for factor construction. After making a factor combination of reduction and construction, AHP is used to calculate the MCR (ϖ_i). Then, we use d_i and B to gain the NBS and PA solution and ϖ_i, d_i, B to get the ABCR solution. The last step is to analyze results.

2.4. The Framework of ABCR. Utilizing the idea of Nash bargaining solution, assuming that cooperative principle is the prerequisite and the next cooperation allocation results can be decided by previous results, and taking into account the difference of member contribution rate in alliance, a fair allocation model can be extended as

$$\max \quad \prod_{i=1}^{m} (x_i - d_i)^{\varpi_i},$$
$$\text{s.t.} \quad \begin{cases} \sum_{i=1}^{m} x_i = B, \\ x_i \geq d_i \quad (i = 1, 2, \cdots, m), \\ \sum_{i=1}^{m} \varpi_i = 1, \end{cases} \tag{1}$$

where B represents the sum of the benefits earned by all members, x_i is the expected allocation of the ith member, d_i is the actual allocation of the ith member in last time, and ϖ_i express the difference of member contribution rate (MCR).

To obtain the solution of model (1), most often we tend to take logarithm of object function, because it will not change the monotonicity. Then model (1) can be changed into

$$\max \quad Z = \sum_{i=1}^{m} \varpi_i \ln (x_i - d_i),$$
$$\text{s.t.} \quad \begin{cases} \sum_{i=1}^{m} x_i = B, \\ x_i \geq d_i \quad (i = 1, 2, \cdots, m) \\ \sum_{i=1}^{m} \varpi_i = 1. \end{cases}, \tag{2}$$

It is easy to obtain the solution of model (3) by the method of Lagrange multipliers, which can be written as

$$x_i = d_i + \varpi_i \left(B - \sum_{i=1}^{m} d_i \right). \tag{3}$$

Remark 3. (1) If $\varpi_i = 1$, model (1) will deteriorate to the following model [15]:

$$\psi(F, v) = \arg\max_{x \in F} \prod_{i \in N} (x_i - v_i). \tag{4}$$

(2) Model (4) has a unique solution if the definitions of F and v are extended to R^N, $N \geq 3$, for a large set of players N, where the set of feasible allocation F is a closed convex subset of R^2 and $v = (v_1, v_2) \in R^2$ is the disagreement or threat point. And $F \cap \{x \mid x \geq v\}$ is nonempty and bounded. In other words, model (4) is a special case of model (1).

(3) Usually, to make the solution convincing, it is needed to consider the role of subcoalitions $S \subseteq N$ of players. Remarkably, it is not meaningful for more than two players for NBS when describing a particular cooperative bargaining game [18].

(4) Model (1), based on assumptions 1 and 2, has a complete theoretical meaning. It is very meaningful for model (1) to display the actual allocation significance by using MCR to describe the contribution of each member.

(5) If the expected allocation of each member is less than that of actual allocation, model (1) can be dealt with the same as

$$\begin{aligned} &\min \quad \prod_{i=1}^{m} (d_i - x_i)^{\varpi_i}, \\ &\text{s.t.} \quad \begin{cases} \sum_{i=1}^{m} x_i = B, \\ x_i \leq d_i \quad (i = 1, 2, \cdots .m), \\ \sum_{i=1}^{m} \varpi_i = 1. \end{cases} \end{aligned} \tag{5}$$

3. The Algorithm of ABCR

3.1. Data Collection and Data Preprocessing. Before implementing a fair allocation by ABCR, certain influencing factors and uncertain influencing factors are all collected firstly. Then the values of certain factors should be normalized and the uncertain factors should be abstracted as a new characteristic factor and quantified.

3.2. Factors Reduction and Factors Construction. Alliance activities are often very complex, as well as the characteristics of members. Factors that affect the contribution of each member are divided into certain factors and uncertain factors.

On the one hand, only a few certain factors play key roles in alliance activities. In order to select the key factors from original certain factors, factors reduction is a necessary process. On the other hand, some uncertain factors may play an important role, too. Therefore, factors construction is also a very important process, which generates one or more key factors from all original uncertain factors. It can be implemented by AHP.

3.3. Member Contribution Rate Calculation. After factor reduction and factor construction, the values of MCR can be obtained by combining the key certain factors and the constructed factors.

The evaluation of MCR is implemented by a quantitative method of DMC based on comparative advantage. The calculation process of MCR can be summed up as follows.

(1) Model the problem as a hierarchy in alliance activities.

(2) Evaluate the hierarchy, which is usually used to express the effect of this hierarchy.

$$K = (k_1, k_2, \cdots, k_m). \tag{6}$$

(3) Establish priorities by determining the weight of each member in alliance.

Assuming that there are m members in alliance, the actual weight of each member in alliance for evaluating the hierarchy is $Q_1, Q_2, \cdots Q_m$. If the number of data and the task are positively correlated, this factor becomes positive and is defined as

$$a_{ij} = \frac{Q_i}{Q_j} \quad (i = 1, 2, \cdots, n, \ j = 1, 2, \cdots, m), \tag{7}$$

where a_{ij} represents the advantage of the i-th member relative to the j-th member.

If the number of data and the task are negatively correlated, this factor becomes negative and is defined as

$$a_{ij} = \frac{Q_j}{Q_i} \quad (i = 1, 2, \cdots, n, \ j = 1, 2, \cdots, m). \tag{8}$$

Thus, we get the comparative advantage matrix of m members as follows:

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mm} \end{pmatrix}. \tag{9}$$

It is easy to see that $A = (a_{ij})_{m \times m}$ has complete consistency. For the positive factor, assuming that the eigenvalue of A is m, the eigenvector of the pth factor is normalized as follows:

$$l_p = \left(\frac{Q_1}{\sum_{i=1}^{m} Q_i}, \frac{Q_2}{\sum_{i=1}^{m} Q_i}, \cdots, \frac{Q_m}{\sum_{i=1}^{m} Q_i} \right)^T. \tag{10}$$

For the negative factor, the eigenvector of the pth factor is normalized as follows:

$$l_p = \left(\frac{1/Q_1}{\sum_{i=1}^{m} (1/Q_i)}, \frac{1/Q_2}{\sum_{i=1}^{m} (1/Q_i)}, \cdots \frac{1/Q_m}{\sum_{i=1}^{m} (1/Q_i)} \right)^T. \tag{11}$$

(4) Contribution Rate Calculation

The contribution rate is calculated as

$$W = K \cdot L, \tag{12}$$

where $L = (l_1, l_2, \cdots, l_p)$.

3.4. The Step of ABCR. According to MCR, the member goal, and the alliance target, the solution of allocation based on MCR is obtained by model (5). Steps of this algorithm are given as below.

Step 1. Model the problem as a hierarchy.

Step 2. Calculate the comprehensive weight of each member's contribution to alliance.

Step 3. Determine the alliance target and the threat points of members.

Step 4. Obtain the fair allocation solution by ABCR.

4. A Fair Allocation Criteria

It is relatively easy to present a variety of possible "fair" allocations, but what is really different is to accurately assess these allocations. In order to illustrate the rationality of our fair allocation algorithm, we have designed the following assessment indicators. It is worth noting that there are no united assessment criteria for a fair allocation algorithm in previous studies.

Definition 4. Given some value d_i, which is the actual allocation of the ith member last time, and the value x_{ij}, which is the expected allocation distributed by the jth allocation algorithm to the ith member, the absolute value of their difference is

$$\varepsilon_{ij} = \left| x_{ij} - d_i \right|, \tag{13}$$

where the vertical bars denote absolute value. If $d_i \neq 0$, the relative ratio is

$$r_{ij} = \left| \frac{x_{ij} - d_i}{d_i} \right| \times 100\% \quad (i = 1, 2, \cdots, m, \ j = 1, 2, \cdots, n). \tag{14}$$

We call this relative ratio the relative growth rate (RGR). r_{ij} represents the RGR of the value assigned by the jth allocation algorithm to the ith member.

Definition 5. Given some value ϖ_i and r_{ij}, the absolute value of their difference is

$$\Delta_{ij} = \left| r_{ij} - \varpi_i \right| \quad (i = 1, 2, \cdots, m, \ j = 1, 2, \cdots, n). \tag{15}$$

We call this difference the fairness degree (FD) of the jth allocation algorithm on the ith member. Δ_{ij} is the magnitude of the difference between its contribution rate and the RGR of the ith member's quantity portion by the jth allocation algorithm. That is to say, the smaller the value of FD is, the closer the relative growth rate and its contribution rate are.

Definition 6. If we have a data set containing the values $\Delta_{1j}, \Delta_{2j}, \cdots, \Delta_{mj}$, which is a group of fairness degrees defined by Definition 5, F_j can be calculated by

$$F_j = \frac{1}{m} \sum_{i=1}^{m} \Delta_{ij}, \quad (j = 1, 2, \cdots, n), \tag{16}$$

where F_j represents the FD of the jth allocation algorithm. We call F_j the mean fairness degree (MFD) of the jth allocation algorithm.

Then, $\exists k \in \{1, 2, \cdots, n\}$, such that $F_k = \arg_{1 \le j \le n} \min F_j$. Our aim is to find such number k such that F_k is the minimum of all the mean fairness degrees. Once we find such number k, we can conclude by the definition of F_k that the kth allocation scheme is the fairest allocation scheme, and the value of F_k gives a measure of its fairness degree.

5. Application on Oil Production Task Allocation

Suppose an oil company has three oilfield branches, the oil production in last year was 1.4012, 2.2618, and 1.6535 million tons, and the oil production task of this oil company in next year is 5.8482 million tons. Some certain effect factors of each oilfield branch can be obtained, such as the production capacity in last year, the number of active wells, the production of old wells, the production cost, the water content, natural decline rate, comprehensive decline rate, and the remaining recoverable reserves (the details are omitted for reasons of confidentiality).

In addition, some uncertain effect factors can be obtained and the details are omitted for the same reasons. There are some main uncertain effect factors, such as the degree of drilling equipment, the level of production management, the geographical location, and technical staff level. The production capacity of each oilfield branch may be quite different. Hence, it is very important to allocate the oil production task to each oilfield branch fairly.

5.1. Calculations to Illustrate the Principle of ABCR. To solve this problem, three steps are taken in ABCR.

Step 5 (determination of main factors). Production capacity and natural decline rate are two main certain factors that are selected from certain effect factors by PAC. Uncertain factors include the location of drilling platform, the equipment level, the technical staff level, and the production management level. The key uncertain factors are extracted by AHP (Figure 2), which we call reality workload (RW).

Step 6 (calculation of member contribute rate). With the main factors, natural production, natural decline rate, and RW of uncertainty factors, the MCR of each branch can be determined by AHP.

Firstly, evaluate the priorities of the criterion layer to the target layer.

After determining the relative importance of the three factors shown in Figure 3 to the branch contribution rate, we need to construct a pairwise comparison matrix. The matrix can be expressed as follows:

$$a_{ij} = \frac{C_i}{C_j}. \tag{17}$$

C_i, C_j are the i-th row factor and the j-th line factor, respectively.

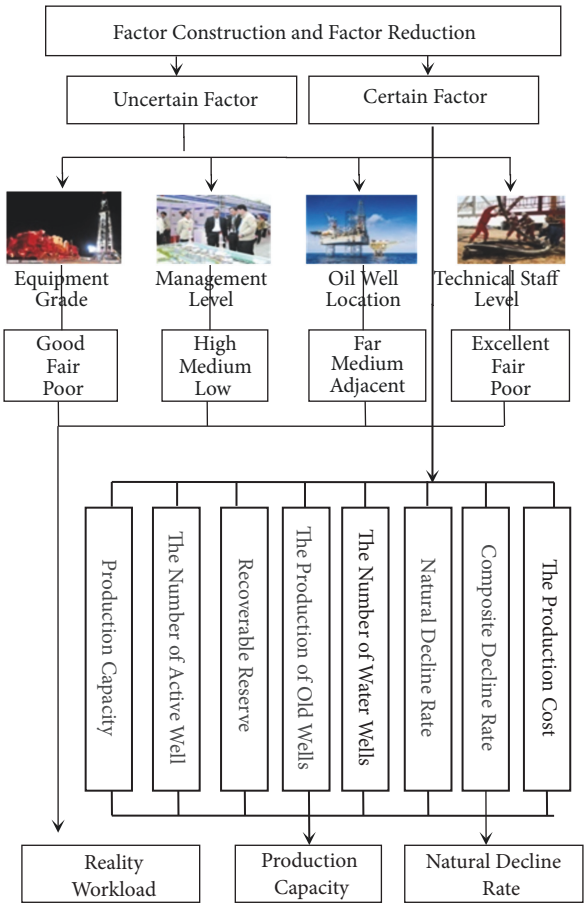

Figure 2: Factor construction and factor reduction.

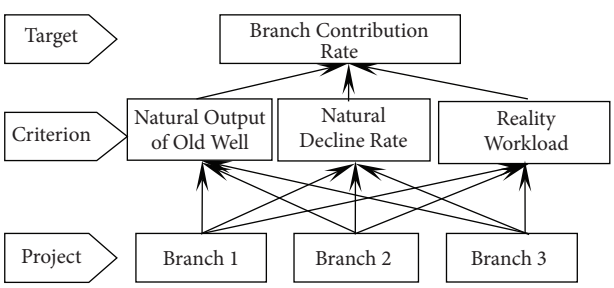

Figure 3: Structure for member weight evaluation.

In this situation, the natural rate of decline and the actual workload are more important. The actual workload refers to the distribution of reservoirs, the geographical location of each branch, the oil company's personnel structure, and other comprehensive factors. The comparison matrix can be calculated as follows:

$$\begin{pmatrix} 1 & \frac{1}{6} & \frac{1}{6} \\ 6 & 1 & 3 \\ 6 & \frac{1}{3} & 1 \end{pmatrix}. \tag{18}$$

To determine the weight of the distribution of natural production in alliance, the corresponding normalized feature vector is

$$W = \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix}^T = \begin{pmatrix} 0.0724 \\ 0.6265 \\ 0.3011 \end{pmatrix}^T. \tag{19}$$

The consistency ratio of this matrix is 0.0171. It means that this matrix can pass the consistency test and is properly to be used for calculation.

Secondly, evaluate the priorities of the project layer to the criterion layer.

According to the actual data, we can compare the relative advantages, but we need to pay attention to the interpretation of the data. In distribution of the old oil well production, the natural production in last year reflects the production capacity of the oil factory. Therefore, the larger the natural production, the larger the production capacity of the oil factory. The natural decline rate reflects the enterprise resources consumption rate, so the lower the natural decline rate, the lower the enterprise resources consumption rate. And the actual workload reflects the benefit of the enterprise, so the smaller the actual workload, the smaller the benefit of the enterprise.

The paired comparison matrixes about three influencing factors in these oil production branch factories are constructed as follows:

① The paired comparison matrixes of three branches to the natural production can be calculated as follows:

$$a_{ij}^1 = \frac{Q_i^1}{Q_j^1} \quad (i, j = 1, 2, 3),$$
$$A^1 = \begin{pmatrix} 1 & 0.62 & 0.847 \\ 1.613 & 1 & 1.368 \\ 1.181 & 0.731 & 1 \end{pmatrix}, \tag{20}$$
$$l_1 = \begin{pmatrix} 0.2636 \\ 0.4253 \\ 0.3111 \end{pmatrix}.$$

② The paired comparison matrixes of three branches to the natural decline rate can be calculated as follows:

$$a_{ij}^2 = \frac{Q_i^2}{Q_j^2} \quad (i, j = 1, 2, 3),$$
$$A^2 = \begin{pmatrix} 1 & 0.321 & 7.447 \\ 3.116 & 1 & 23.203 \\ 0.134 & 0.043 & 1 \end{pmatrix}, \tag{21}$$
$$l_2 = \begin{pmatrix} 0.2353 \\ 0.7331 \\ 0.0316 \end{pmatrix}.$$

Table 1: Member contribution rate calculation.

No. branch	Selected factors: Natural production of old well (unit: million tons)		Natural decline rate	Constructed factors: Actual workload		Member contribution rate
	Value	Proportion		Value	Proportion	
1	1.4012	0.2636	2.15%	200	0.3333	0.2626
2	2.2618	0.4254	*0.69%*	250	0.4167	0.5669
3	1.6535	0.3110	**16.01%**	150	0.2500	0.1676

Table 2: NPOW allocations of PA, NBS, and ABCR.

No.	NPOW of last year	Results of fair allocation (B=5.8482, unit: million tons)								
		PA			NBS			ABCR		
		Value (x_{i1})	RGR (r_{i1})	Δ_{i1}	Value (x_{i2})	RGR (r_{i2})	Δ_{i2}	Value (x_{i3})	RGR (r_{i3})	Δ_{i3}
1	1.4012	1.5413	0.1	0.162	1.9434	0.387	0.1244	1.5961	0.1391	0.1235
2	2.2618	2.4880	0.1	0.4669	2.3210	*0.0261*	0.5407	2.3778	0.0513	*0.5156*
3	1.6535	1.8189	0.0987	0.069	1.5838	**−0.0433**	0.1243	1.8743	0.1335	0.034

③ The paired comparison matrixes of three branches to the actual workload can be calculated as follows:

$$a_{ij}^3 = \frac{Q_i^3}{Q_j^3} \quad (i, j = 1, 2, 3),$$

$$A^3 = \begin{pmatrix} 1 & 1.25 & 0.6 \\ 0.8 & 1 & 0.6 \\ 1.667 & 1.667 & 1 \end{pmatrix}, \tag{22}$$

$$l_3 = \begin{pmatrix} 0.319 \\ 0.255 \\ 0.416 \end{pmatrix}.$$

Thirdly, the calculation of MCR.

The MCRs of three oil branches are calculated as follows:

$$W = (k_1, k_2, k_3) = K \cdot L = (0.0724, 0.6265, 0.3011) \cdot \begin{pmatrix} 0.2636 & 0.2353 & 0.319 \\ 0.4253 & 0.7331 & 0.255 \\ 0.3111 & 0.0316 & 0.416 \end{pmatrix}^T = (0.2626, 0.5669, 0.1676). \tag{23}$$

Step 7 (the allocation of oil production task). Table 1 shows the proportion of certain factors, uncertain factors, and some relative values.

After obtaining these data, the allocations of ABCR, NBS, and PA were obtained, respectively. The allocation values and their RGR are shown together in Table 2.

5.2. Results Analysis Based on the MFD. It can be seen from Table 2 that mean fairness degrees of 3 methods are $F_1 = 0.6976$, $F_2 = 0.7894$, and $F_3 = 0.6731$. And F_3 is the smallest. This implies that the ABCR solution is the best among these three algorithms.

Table 3: The characteristics of fair allocations algorithm.

	Characteristics	Level
PA	(1) Member goal and alliance target are needed (2) The growth rates tend to equal and are much different from the trend of weight change	A
NBS	(1) Member goal and alliance target are needed (2) The growth rates have too many differences and are much different from the trend of weight change; there even exist negatives	A
ABCR	(1) Beside member goal and alliance target, member weights are also needed (2) The growth rate is related to the trend of weight change	A+

Furthermore, comparing the results of these three different algorithms, it can be found that the best result can be obtained by multiple factors allocation. The results of three methods are compared in Table 3.

The main advantages of ABCR are summed up as follows:

(1) Avoiding irrational proportional allocation. For example, suppose oil company sets a course for 10% growth compared with the production in last year. The natural decline rate of the No. 3 branch is the highest. The value is 16.01% (boldfaced in Table 1). This means that there are more poor oil wells in the No. 3 branch than those of the other oil branches. However, according to the proportional allocation, the production task still needs to increase by 10%, and the Nash bargaining solution shows that the production task needs to decrease by 4.33% (boldfaced in Table 2). Therefore, it is more reasonable that the production task obtained by multiple factors allocation needs to increase by 3.41% (boldfaced in Table 2).

(2) When compared with NBS, it is easier for ABCR to release potential of production capacity in strong branches. In fact, the actual production capacity of the No. 2 branch is 16.18% higher than that of the No. 1 branch. However,

according to the allocation result of Nash bargain solution, the production task of the No. 2 branch is only 6.46% higher than that of No. 1 branch.

(3) Also, suppose oil company sets a course for 10% growth compared with the production in last year and the natural decline rate of the No. 2 branch is the lowest. The valve is 0.69% (italicized in Table 1). This means that there are more rich oil wells in the No. 3 branch than those of the other oil branches. The production task still needs to increase by 10% according to the proportional distribution, while the Nash solution only needs to increase by 2.61% (italicized in Table 2), but the production task obtained by multiple factors allocation needs to increase by 51.56% (italicized in Table 2). It means that ABCR stimulates the potential of production capacity in strong branches, and this allocation algorithm is more reasonable.

6. Conclusion and Future Work

This paper presents a fair allocation algorithm called ABCR. In this algorithm, we consider three elements of fair allocation: member contribute rate, member goal, and alliance target. In order to determine the member contribution rate, we divide the factors that affect fair allocation into two categories: certain factors and uncertain ones. We get the main certain factors by PCA, get the overall uncertain factors by AHP, and then combine them to determine the member contribution rate of each member in alliance activities. In addition, in order to assess the fairness of this proposed algorithm, a criterion evolution method for fairness is proposed. In case study, actual production data is applied to three different allocation algorithms, the results of which show that the rationality of our fair allocation algorithm is the best. Finally, we justify our fair allocation algorithm by comparing its characteristics with those of the other two allocation algorithms.

There were two main research motivations that drove this work. The first motivation is whether there exists a fair allocation algorithm to characterize variable or uncertain factors. To the best of our knowledge, ABCR is a rational solution to tackle this problem. The second motivation is that there exist many studies about fair allocation, but there is less discussion about fairness criteria evaluation. Therefore, we present an easy fairness criteria evaluation method and a case study shows that our proposed fairness allocation algorithm is rational.

To summarize, this work makes an in-depth study of certain and uncertainties factors that affect production task, as well as using factor selection and factor construction to determine the main factors that affect production task to determine the contribution rate of members in affiliate activities, combined with member goals and alliance target to determine the results of fair allocation. Based on the adaptation scenario of the fair allocation algorithm, we believe that this proposed allocation algorithm is very suitable in practice. Nevertheless, considering the results of this work, we believe that a more complex scenario also needs this model to distribute the oil production task, so it is very meaningful to extend the domain of the proposed model to other application scenarios, such as the multi-league cooperation allocation problem.

Data Availability

Some data were omitted due to a confidentiality agreement between the research team and the Northwest Oil Field Branch, China Petroleum & Chemical Corporation. The signed agreement is valid from December 18, 2012, to December 17, 2021.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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References

[1] K. Shen, X. Zheng, Y. Song, and Y. Bai, "Fair multi-node multi-resource allocation and task scheduling in datacenter," in *Proceedings of the IEEE Asia Pacific Cloud Computing Congress (APCloudCC)*, pp. 59–63, Shenzhen, China, November 2012.

[2] Q. Baert and A. C. Caron, "Fair Multi-agent Task Allocation for Large Data Sets Analysis," in *Proceedings of the 14th International Conference on Practical Applications of Agents and Multi-Agent Systems*, Sevilla, Spain, 2016.

[3] J. Chen, C. H. Wang, and Z. M. Zhao, "Uncovering the Face of Android Ransomware: Characterization and Real-time Detection," *IEEE Transactions on Information Forensic Security*, vol. 13, pp. 1286–1300, 2018.

[4] J. Chen, K. He, Q. Yuan, G. Xue, R. Du, and L. Wang, "Batch Identification Game Model for Invalid Signatures in Wireless Mobile Networks," *IEEE Transactions on Mobile Computing*, vol. 16, no. 6, pp. 1530–1543, 2017.

[5] J. Gallien and L. M. Wein, "A smart market for industrial procurement with capacity constraints," *Management Science*, vol. 51, no. 1, pp. 76–91, 2005.

[6] K. He, J. Chen, R. Du, Q. Wu, G. Xue, and X. Zhang, "DeyPoS: Deduplicatable Dynamic Proof of Storage for Multi-User Environments," *IEEE Transactions on Computers*, vol. 65, no. 12, pp. 3631–3645, 2016.

[7] A. M. Campbell, D. Vandenbussche, and W. Hermann, "Routing for relief efforts," *Transportation Science*, vol. 42, no. 2, pp. 127–145, 2008.

[8] D. Bertsimas, V. F. Farias, and N. Trichakis, "On the efficiency-fairness trade-off," *Management Science*, vol. 58, no. 12, pp. 2234–2250, 2012.

[9] A. Osório, "Self-interest and equity concerns: a behavioural allocation rule for operational problems," *European Journal of Operational Research*, vol. 261, no. 1, pp. 205–213, 2017.

[10] S. Kim, "Inspection game based cooperative spectrum sensing and sharing scheme for cognitive radio IoT system," *Computer Communications*, vol. 105, pp. 116–123, 2017.

[11] S. Kim, "Adaptive Cognitive Radio Energy-harvesting Algorithm Using Sequential Game Approach," *Eurasip journal on wireless communications and networking*, vol. 16, 2017.

[12] L. S. Shapley, "A Value for n-persons Games," in *Contributions to the Theory of Games*, vol. 2 of *Annals of Mathematics Studies, No. 28*, pp. 307–317, Princeton University Press, Princeton, NJ, USA, 1953.

[13] L. S. Shapley, "On Balanced Games Without Side Payments," in *Proceedings of an Advanced Seminar Conducted by the Mathematics Research Center*, The University of Wisconsin, The U. S. Army, 1972.

[14] G. Owen, "Multilinear extensions of games," *Management Science*, vol. 18, pp. 64–79, 1972.

[15] D. B. Gillies, "Solutions to general non-zero-sum games," in *Contributions to the theory of games, Vol. IV*, Annals of Mathematics Studies, no. 40, pp. 47–85, Princeton University Press, Princeton, NJ, USA, 1959.

[16] T. Murofushi and S. Soneda, "Techniques for Reading Fuzzy Measures (III): Interaction Index," in *Proceedings of the Fuzzy System Symposium*, pp. 693–696, Sapporo, Japan, 1993.

[17] I. Kojadinovic, "Relevance measures for subset variable selection in regression problems based on k-additive mutual information," *Computational Statistics & Data Analysis*, vol. 49, no. 4, pp. 1205–1227, 2005.

[18] H. J. M. Peters, "Axiomatic Bargaining Game Theory," *Econometrica*, vol. 9, 1992.

[19] A. M. Mármol, L. Monroy, and V. Rubiales, "An equitable solution for multicriteria bargaining games," *European Journal of Operational Research*, vol. 177, no. 3, pp. 1523–1534, 2007.

[20] V. Venugopal and T. T. Narendran, "An interactive procedure for multiobjective optimization using nash bargaining principle," *Decision Support Systems*, vol. 6, no. 3, pp. 261–268, 1990.

[21] P. E. Dunne, S. Kraus, E. Manisterski, and M. Wooldridge, "Solving coalitional resource games," *Artificial Intelligence*, vol. 174, no. 1, pp. 20–50, 2010.

[22] K. Pearson, "LIII. On lines and planes of closest fit to systems of points in space," *Philosophical Magazine*, vol. 2, no. 11, pp. 559–572, 1901.

[23] T. L. Saaty, *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*, McGraw-Hill, New York, NY, USA, 1980.