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A multi-objective optimization approach for the selection of overseas oil projects

Hao Chen [a,d,*], Xi-Yu Li [b], Xin-Ru Lu [b], Ni Sheng [c], Wei Zhou [d], Hao-Peng Geng [b], Shiwei Yu [b]

[a] School of Applied Economics, Renmin University of China, Beijing 100872, China
[b] School of Economics and Management, China University of Geosciences, Wuhan 430074, China
[c] School of Business, Macau University of Science and Technology, Macao 999078, China
[d] Energy Policy Research Group (EPRG), University of Cambridge, Cambridge CB2 1AG, UK

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ABSTRACT

Most good quality overseas oil projects, high in investment returns and abundant in resources, are located in politically unstable regions, where competing objectives present great challenges for investors to make informed decisions. Moreover, most of the existing models are single objective and do not adequately incorporate the unique characteristics of overseas oil investment. To bridge these gaps, this study develops a Non-linear Multi-objective Binary Program (NMBP) to optimize the investment portfolios under three competing objectives. A solution algorithm is developed to solve this multiple objective program by integrating Non-dominated Sorting Genetic Algorithm II (NSGA-II) with Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). NSGA-II searches for the pareto set of optimal investment portfolios and TOPSIS determines the best compromise solution based on the investors' preferences. Finally, China's oil investment in the Belt and Road Initiative countries is taken as a case study to demonstrate the feasibility and effectiveness of the proposed approach.

1. Introduction

Global oil resources are geographically unevenly distributed and the mismatch between supply and demand motivates the business of overseas oil investment (Fan & Zhu, 2010; Tan & Barton, 2017). For a long time, international oil majors have been actively engaging in overseas oil investments. As a result, many good quality oil fields, characterized by high profitability and low risks, have already been under the control of International Oil Companies (IOCs), or National Oil Companies (NOCs) due to the nationalization of the oil industry (Bhattacharyya, 2019; Hu, Hall, Wang, Feng, & Poisson, 2013; Mahdavi, 2014). Many oil projects currently being tendered in the global market are located in countries where wars, geopolitical events and conflicts occur frequently, posing great political risks for investment decisions (Plakandaras, Gupta, & Wong, 2019; Vermeer, 2015). Political risks can adversely affect overseas investments in various forms, such as oil price fluctuations, destroyed oil field infrastructure, injured employees, and amendment or cancellation of contracts (Chen, Liao, Tang, & Wei, 2016; Lambrechts & Blomquist, 2017; Smimou, 2014; Van de Putte, Gates, & Holder, 2012; Wang, Sun, Li, Chen, & Liu, 2018). The ramification can be tremendous economic losses or even as serious as bankruptcy of investors. Apart from the high risk, investments in oil projects feature high capital-intensity, strict irreversibility and long-term lock-in. All these critical factors shall be adequately identified and evaluated by prudent investors, whose principal interest is anchored in allocating their limited resources into the most valuable portfolios (Duan, Ji, Liu, & Fan, 2018; Zhu, Zhang, & Fan, 2015). Fundamentally, the portfolio choice is a typical multi-objective optimization problem, which requires several competing objectives (i.e. profit maximization, resource maximization and risk minimization) to be balanced simultaneously (Alvarezgarcia & Fernandezcastro, 2018; Khalilidamghani & Sadinezhad, 2013).

Optimizing portfolio choices under multiple objectives is a popular research topic in many fields. Markowitz (1952) proposed the first 'mean-variance' portfolio selection model. It uses binary variables to represent the investment decisions of different stocks, and then optimizes the decisions considering two competing and incommensurable criteria (investment return and risk). Since then, this model framework has been commonly used for portfolio optimization in a wide variety of contexts, such as stock market, bond market, pharmaceutical industry and electricity sector (Bekiros, Hernandez, Hammoudeh, & Nguyen,

* Corresponding author at: School of Applied Economics, Renmin University of China, Beijing 100872, China.
E-mail addresses: chenhao9133@126.com (H. Chen), addxiyu@cug.edu.cn (X.-Y. Li), xinrulu@163.com (X.-R. Lu), nis@must.edu.mo (N. Sheng), wz282@cam.ac.uk (W. Zhou), ghp926@cug.edu.cn (H.-P. Geng), ysw81993@sina.com (S. Yu).

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Table 1
Definitions of the sets, indices, parameters and variables.

Symbols	Explanations	Symbols	Explanations
Sets and indices		QA_i	Project's oil quality
i, i'	Project index	QA_b	Lower limit of oil quality
j	Algorithm iteration index	***NSGA-II parameters***	
r	Frontier index in crowded sorting	P_j	Father generations
k, k'	Constraint index	S_j	Offspring generations
t	Year index	NC_j	Newly combined generations
m	Solution index	P_s	Population size
l	Objective function index	F_k	k th non-dominated frontier
T	Investment planning period	p_c	Probabilities of crossover
RK_q	Project sets of different regions	p_m	Probabilities of mutations
RC_l	Project sets of different contract types	$Maxgen$	Maximum iteration number
RO_e	Project sets of different landscapes	$G_1^{(mk)}, G_t^{(mk)}$	k th group constraint violations
Ω	Set of bundled investment projects	$\overline{G}_1^{(mk)}, \overline{G}_t^{(mk')}$	Normalized values of the k th group constraint violations
Ψ	Set of mutually exclusive investment projects	$VC^{(m)}$	Total normalized constraint violations of solution m
Φ	Set of strategic investment projects	CD	Center distance of the pareto solutions
NMBP parameters		GC	Gravity center of the obtained Pareto solutions
N	Total project numbers	O	Original point (0,0,0)
NPV_i	Net present values	SD	Spacing distance of the pareto solutions
TQ_i	Total oil production in the planning period	M	Total number of solutions in the frontier
R_i	Project political risk index	$\overline{ds}$	Average value of all Euclidean distances
OR_i	Total remaining oil reserves	ds_m	Euclidean distance between solution m and its nearest neighbor solution
I_i	Project's investment cost	***TOPSIS parameters***	
B	Investment cost budget	f_{ml}	l th objective function value of solution m
C_i	Project's unit operation cost	z_{ml}	Normalized objective function values
$Q_{i,t}$	Project's annual oil production	ω_l	Weights of the objective function l
$C_{b,t}$	Limit of total operation cost	h_{ml}	Weighed values of the objective function l
IRR_i	Project's IRR	h_m^*	Positive ideal investment portfolio
IRR_b	Lower limit of IRR	h_m^0	Negative ideal investment portfolio
TN	Maximum project number	d_m^*	Dirichlet distance of every portfolio from the positive ideal solution
GN_q	Lower limit of project numbers in different resource regions	d_m^0	Dirichlet distance of every portfolio from the negative ideal solution
CN_l	Lower limit of project numbers of different contract types	PR_m^*	Portfolio rank index
SN_e	Lower limit of project numbers of different land locations	***Decision variables***	
D_t	Annual equity oil demand	x_i	Project investment decisions

2015; Capponi & Figueroa-López, 2014; Choi, 2015; Gatica, Papageorgiou, & Shah, 2003; Liu & Wu, 2007; Vithayasrichareon & MacGill, 2012). However, only a small number of studies have applied it to overseas oil investment. This is mainly because adequate and reliable data on comparable candidate projects is not easily accessible, as most oil companies treat the oil project data as strictly confidential (Yan & Ji, 2018). Tang, Zhou, and Cao (2017) used a portfolio optimization technique to analyze the portfolio choices in the overseas oil investment. Xue, Wang, Liu, and Zhao (2014) proposed an improved portfolio optimization model for oil and gas investment selection by considering the trade-offs between returns and risk. Yan and Ji (2018) developed an optimization model of oil project selections considering the uncertainties of the investment environment.

The previous studies of overseas oil investment can be improved from both the model formulation aspects and the empirical application aspects. First, although using the mean-variance framework, most existing oil investment models are formulated as single objective optimization models. They subjectively convert either the risk objective or the investment return objective into a constraint of the optimization model, neglecting the nature of oil investment under multiple objectives. However, the concept of pareto optimality is suitable for this multi-objective problem, which can effectively balance all the competing objectives.[1] Second, most models use the same constraint types as the traditional mean-variance models in the securities market, very few studies have integrated the unique characteristics of overseas oil investment. For example, the bidding rules in the securities market and the oil project market differ a lot, some oil projects have bundled constraints or exclusive constraints imposed by the resource countries due to political and diplomatic considerations. Moreover, the outcomes of overseas oil investment depend on the projects' contract types (Zhao, Luo, & Xia, 2012). Investors can obtain both equity oil and economic returns from Concession Contracts and Production Share Contracts

[1] A pareto optimal solution indicates that the solution is strictly better from at least one aspect. Moreover, none of the objective functions of the pareto optimal solution can be improved in value without degrading some of the other objective values. Therefore, the concept of pareto optimality is more appropriate to determine whether one solution is better relative to other solutions in the multi-objective overseas oil investment.

(PSC), but they are only entitled to economic benefits from Buy-back Contracts or Service Contracts. Finally, most studies only qualitatively describe the political situation in the resource countries, with few of them quantifying the political risks into their models. However, several indices can be used to represent the political risks of projects' investment environment, such as the International Country Risk Guide (ICRG) index published by the Political Risk Service (PRS) Group, the Forelend Index issued by Business Environment Risk Intelligence (BERI), the country risk rating index released by the Japan Bond Research Institute (JBRI), and the country risk index ranking table developed by Euromoney. Amongst these indices, ICRG is preferred, given the index application domain, influence and data updating frequency (Chen et al., 2016). ICRG index has been published monthly since 1984. It has a value ranging from 0 to 100, with lower values indicating higher political risks. Moreover, ICRG index has already been used in the strategic planning in oil import optimization and country risk assessment (Fan & Zhu, 2010; Kong et al., 2019). Thus, the ICRG index is used in this study as a proxy to reflect oil projects' political risks. Finally, few studies have analyzed the portfolio choices of overseas oil investment in the Belt and Road (B&R) countries, but it is one of the most important cooperation areas under Belt and Road Initiative (BRI) proposed by the Chinese government.

This study develops a Non-linear Multi-objective Binary Program (NMBP) model with methodological and empirical advances across the above-mentioned four aspects. Three competing objectives are addressed by the model, including profit maximization, resource maximization and risk minimization. Moreover, nine categories of constraints are considered in the model to capture the unique characteristics of the overseas oil investment. Then, a solution algorithm integrating Non-dominated Sorting Genetic Algorithm II (NSGA-II) with Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is developed to solve the model. A set of pareto optimal solutions is generated from NSGA-II, while the TOPSIS is further employed to choose the best compromise solution. Finally, China's overseas oil investment in the Belt and Road (B&R) countries is taken as an example where the established model and algorithm framework are applied to analyze the spatial distributions, production profiles and sensitivity of the investment portfolios.

The remainder of this paper is organized as follows. Sections 2 and 3 elaborate the NMBP model and the NSGA-II-TOPSIS solution algorithm for solving the model, respectively. Section 4 describes the data and assumptions of the case study of China's overseas oil investment in the B&R countries. Section 5 provides the result analysis of the empirical studies. Section 6 summarizes and concludes and paper.

2. Problem description and model formulation

Investors make overseas oil investments to get profits and gain international operation experiences. To this end, a major task for investors is to choose the best possible investment portfolios from a large set of tendered projects for the planning period. Modelling plays a key role in enabling investors to undertake a holistic and in-depth analysis to find out what could be the potential optimal outcome under all relevant objectives and constraints, based on which informed investment decisions can be made. To provide guidance for the overseas oil investment, a NMBP model is developed by this study. The definitions of the sets, parameters and variables used in the model are shown in Table 1.

Several assumptions have been made for the overseas oil investment optimization model. 1) All the investment decisions should be made at the starting point of the planning period. 2) The investment decisions of projects are irreversible. 3) The parameters concerning the oil projects, such as oil prices, cash flows, costs and profits, are based on asset analysis reports and have already been owned by investors before the decisions. 4) All the capital costs are assumed to be paid at the starting point of the planning period, and the Operation & Maintenance (O&M) costs are paid annually.

2.1. Objective functions

The three objectives considered in the overseas oil investment are maximization of profits, minimization of risk and maximization of oil reserves.

(1). **Maximization of profits**. As with the common investment activities, overseas oil investments are profit driven. Investors seek to optimize the investment portfolio to maximize the profits, see equation (1). $x_i$is the binary variable of the investment decision. $x_i = 1$ denotes that a project will be invested, $x_i = 0$indicates that a project will be cancelled.

$$max\, f_1 = \sum_{i=1}^{N} NPV_i \cdot x_i \tag{1}$$

(2). **Minimization of risk**. The successful investment and operation of oil projects is conditional on a stable working environment. Major geopolitical events can cause interruption or termination of oil projects. Therefore, it is desirable to obtain an investment portfolio with lowest possible political risks to ensure smooth production and operation. The objective function which minimizes the production-weighted risk is shown in equation (2).

$$min\ \ f_2 = \sum_{i=1}^{N} TQ_i \cdot R_i \cdot x_i / \sum_{i=1}^{N} TQ_i \cdot x_i \tag{2}$$

(3). **Maximization of oil reserves.** Crude oil is an indispensable energy resource in the global energy mix over the long term. Achieving more oil resources in the investment portfolios is a good approach for ensuring the domestic energy security of the investors. This is especially important for countries with high oil import dependency. Moreover, the more crude oil resources a project has, the more likely that future cooperation can be continued once the original contracts finishes. Therefore, investors want to maximize the oil reserves in the investment portfolios, see equation (3).

$$max\ \ f_3 = \sum_{i=1}^{N} OR_i \cdot x_i \tag{3}$$

2.2. Constraints

Due to the limitations of economy, technology, environment and management resources, the investment portfolios of oil projects face a wide spectrum of constraints. This study considers nine types of constraints in forming the investment portfolios.

(1). **Investment budget constraint**. Based on an investor's strategies and plans, the total budget for investment is limited. The total investment cost of the project portfolio should be within the predetermined budget, see equation (4).

$$\sum_{i=1}^{N} I_i \cdot x_i \leqslant B \tag{4}$$

(2). **Operational cost constraint.** The operational cost of oil fields is a large expenditure during the planning horizon. A high operational cost will adversely affect the liquidity and stability of the investor's cash flow. Therefore, an upper limit is set for the investment portfolio's total operational cost, see equation (5).

$$\sum_{i=1}^{N} C_i \cdot Q_{i,t} \cdot x_i \leqslant C_{b,t} \tag{5}$$

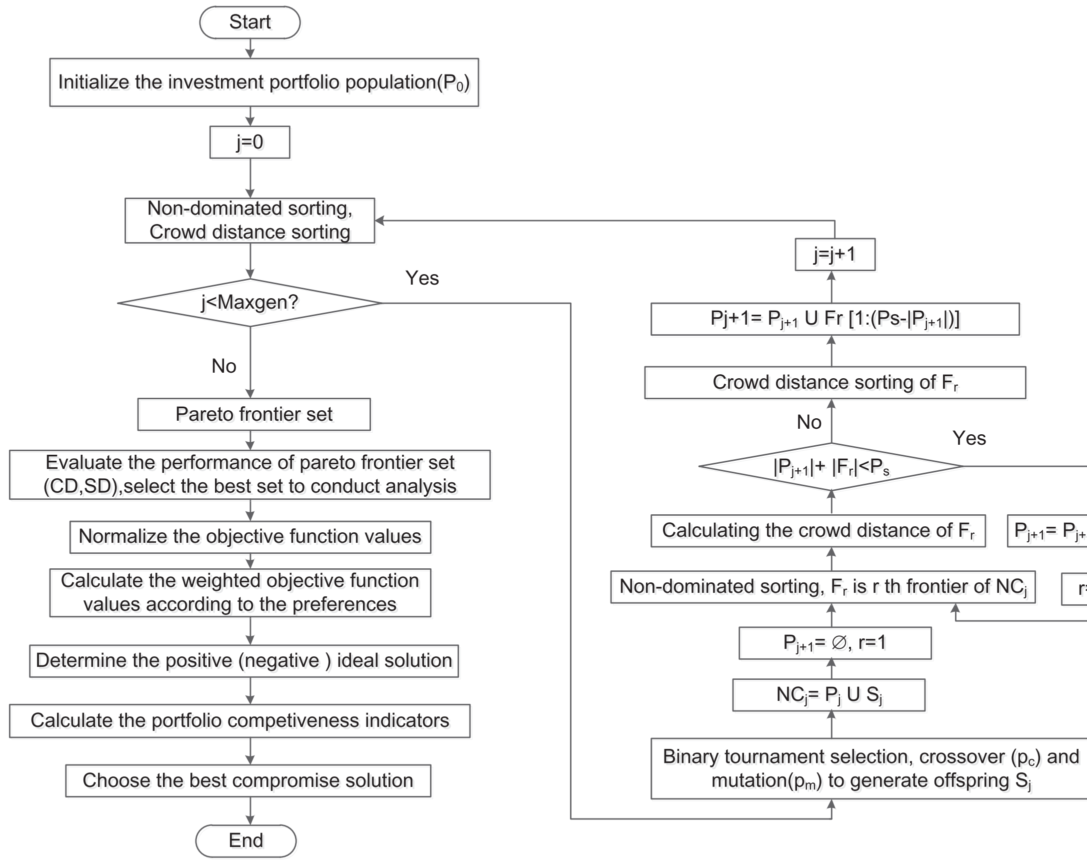

Fig. 1. The procedure of NSGA-II-TOPSIS solution algorithm.

(3). **Investment rate of return constraint.** Overseas oil investment is risky and capital intensive, the project's profitability is a core indicator in deciding whether it should be included in the portfolio or not. In this study, the Internal Rate of Return (IRR) is selected to represent the project profitability, and only the project with IRR values higher than the predetermined value can be selected in the investment portfolios, see equation (6).

$$IRR_i \cdot x_i \geqslant IRR_b \tag{6}$$

(4). **Total project number constraint.** Unlike domestic oil projects, the requirements of operations and management of overseas oil projects are high. The investor's overseas operational team should not only be proficient in the oil investment business, but also be familiar with local policies, language, culture and customs. However, the number of skilled workers is subject to certain limit in reality, so the investor will only be able to invest into a certain number of projects, see equation (7).

$$\sum_{i=1}^{N} x_i \leqslant TN \tag{7}$$

(5). **Diversification constraint.** Diversification is an important approach to mitigate the investment risk. Three types of diversification have been considered in this study. First, there are five major oil resource regions in the world, namely the African region, Central Asia region and Russia region, Middle East region and the Asian-Pacific region. The oil resources, fiscal regimes and political risks differ a lot across these regions. Therefore, minimum numbers of invested projects are set for different regions to ensure that they are spread across all the resource regions, see equation (8). Second, the contracts signed between the investors and resource countries depend on the fiscal regimes. There are four main contract types in the world, including Concession Contract, PSC, Buy-back Contract and Service Contract. The provisions under different contract types can make significant difference to a project's profits and risks. Therefore, in order to manage the risks, every contract type should be invested for at least some numbers of projects, see equation (9). Third, oil projects are either onshore or offshore from a geographical perspective, thereby having very different technical requirements and profitability. For an investor to mitigate the risks and to accumulate investment experiences of different project types, lower limits are set for the numbers of both onshore and offshore projects, see equation (10).

$$\sum_{i \in RK_q} x_i \geq GN_q \quad q = Africa, Central\ \ Asia\&Russia, Middle\ \ East, Asian-Pacific \tag{8}$$

$$\sum_{i \in RC_l} x_i \geqslant CN_l \quad l = PSC, Concession, Service, Buy\text{ - }back \tag{9}$$

$$\sum_{i \in RO_e} x_i \geqslant SN_e \quad e = Onshore, Offshore \tag{10}$$

(6). **Annual equity oil production constraint.** Overseas oil investment is regarded as an approach to reduce oil dependency, as the equity oil resources are under control of the investors. Investors can transport the produced equity oil back to their home countries if necessary. Therefore, annual total production of equity oil is set for the investment portfolio, which defines the minimum amount of annual oil production during the planning horizon, see equation (11).

$$\sum_{i=1}^{N} Q_{i,t}\cdot x_i \geqslant D_t \tag{11}$$

(7). **Oil quality constraint.** With the strict regulations of environmental pollutions, the quality of oil projects has become an important investment constraint. Oil quality can affect the refinery process and cost, thus affecting the investment returns and environmental compliance. In this study, the index published by American Petroleum Institute (API) is selected to comprehensively represent for the oil quality, with a higher API value performing better in quality. Moreover, only a project with API value higher than the threshold value will be eligible for investment consideration, see equation (12).

$$QA_i\cdot x_i \geqslant QA_b \tag{12}$$

(8). **Strategic investment constraint.** Oil investment is an important area to strengthen the international cooperation. Oil resource transaction is often used as a diplomatic practice by the resource countries to solicit political, economic and financial supports from other countries. Therefore, some strategic oil projects (Φ) should be invested regardless of oil projects' other characteristics, see equation (13).

$$x_{i\in\Phi} = 1 \tag{13}$$

(9). **Special bidding rule constraint.** In the global oil market, some resource countries impose special bidding rules for oil projects (Bhattacharyya, 2019). For example, some projects are under the rules of bundled bidding due to their geographical vicinity. This means that these bundled projects (Ω) should be either invested or cancelled collectively, see equation (14). In addition, some projects are mutually exclusive (Ψ), which indicates that investing in one project means the cancelation of other projects, see equation (15).

$$x_{i\in\Omega} = x_{i'\in\Omega} \tag{14}$$

$$x_{i\in\Psi} = 1 - x_{i'\in\Psi} \tag{15}$$

3. NSGA-II-TOPSIS solving algorithm

3.1. Algorithm framework

Since the established overseas oil investment optimization model is a Non-linear Multi-objective Binary Program, it is difficult to be solved by traditional algorithms. Thus, a new solution algorithm is developed by integrating NSGA-II and TOPSIS, whose solution procedure is diagrammatically shown in Fig. 1. The NSGA-II-TOPSIS algorithm consists of two main parts. The first one is NSGA-II which works out the pareto frontier of the optimal investment solutions. The second one is TOPSIS which selects the best compromise solution from the pareto frontier obtained from the NSGA-II. The details of these two components are described in Sections 3.2 and 3.3.

3.2. NSGA-II algorithm

NSGA-II, proposed by Deb, Pratap, Agarwal, and Meyarivan (2002), is a popular solution algorithm for the non-linear multi-objective optimization models. The main procedure of NSGA-II can be described as follows. It firstly initializes the population (P_0) of the investment portfolios. Then, the population will conduct non-dominated sorting and crowd distance sorting. After that, tournament selection, crossover and

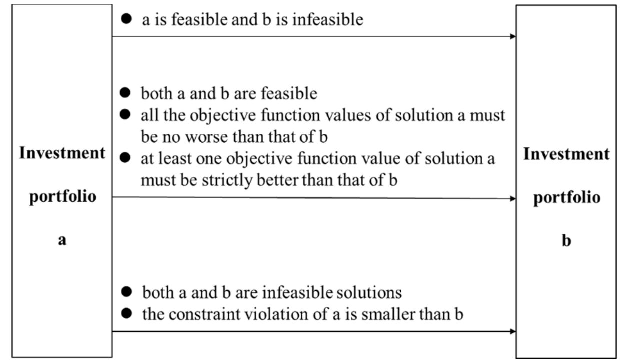

Fig. 2. Domination definitions between solution a and b.

mutation will be applied to the population, to generate the offspring investment portfolio S_0. The top P_s investment portfolios from the combinations of initial population P_0 and offspring population S_0 will be selected to form the next father generation. This loop process will continue until the stop conditions are met. Given that NSGA-II is a relatively mature evolutionary algorithm, we will only describe the special non-dominated sorting rule of different investment portfolios used in this study, other common details can be referred to Deb et al. (2002) and Wang, Fu, Huang, Huang, and Wang (2017).

Considering two investment portfolios (a and b) obtained from the algorithm solution process, the domination rule between these two solutions is defined in Fig. 2. There are three cases that a dominate b, and the corresponding requirements are summarized for each case. It is easy to determine whether a dominate b or not in the first two cases, but the third case depends on the constraint violations of the investment portfolios.

There are three steps in calculating the constraint violations. At first, the violation of every constraint in the optimization model is calculated for a given solution m, see equation (16).

$$\begin{aligned}
G_1^{(m1)} &= max\,(\sum_{i=1}^{N} I_i\cdot x_i - B, 0)\\
G_t^{(m2)} &= max\,(\sum_{i=1}^{N} C_i\cdot Q_{i,t}\cdot x_i - C_{b,t}, 0)\\
G_1^{(m3)} &= max\,(IRR_b - IRR_i\cdot x_i, 0)\\
G_1^{(m4)} &= max\,(\sum_{i=1}^{N} x_i - TN, 0)\\
G_1^{(m5)} &= max\,(GN_q - \sum_{i\in RK_q} x_i, 0)\\
G_1^{(m6)} &= max\,(CN_l - \sum_{i\in RC_l} x_i, 0)\\
G_1^{(m7)} &= max\,(SN_e - \sum_{i\in RO_e} x_i, 0)\\
G_t^{(m8)} &= max\,(D_t - \sum_{i=1}^{N} Q_{i,t}\cdot x_i, 0)\\
G_1^{(m9)} &= max\,(QA_b - QA_i\cdot x_i, 0)\\
G_1^{(m10)} &= max\,(|x_{i\in\Phi} - 1|, 0)\\
G_1^{(m11)} &= max\,(|x_{i\in\Omega} - x_{i'\in\Omega}|, 0)\\
G_1^{(m12)} &= max\,(|x_{i\in\Psi} + x_{i'\in\Psi} - 1|, 0)
\end{aligned} \tag{16}$$

Then, the calculated constraint violations are normalized because these constraints vary in the units and scales, see equation (17). After the normalization, all the constraint violations will have values ranging from 0 to 1.

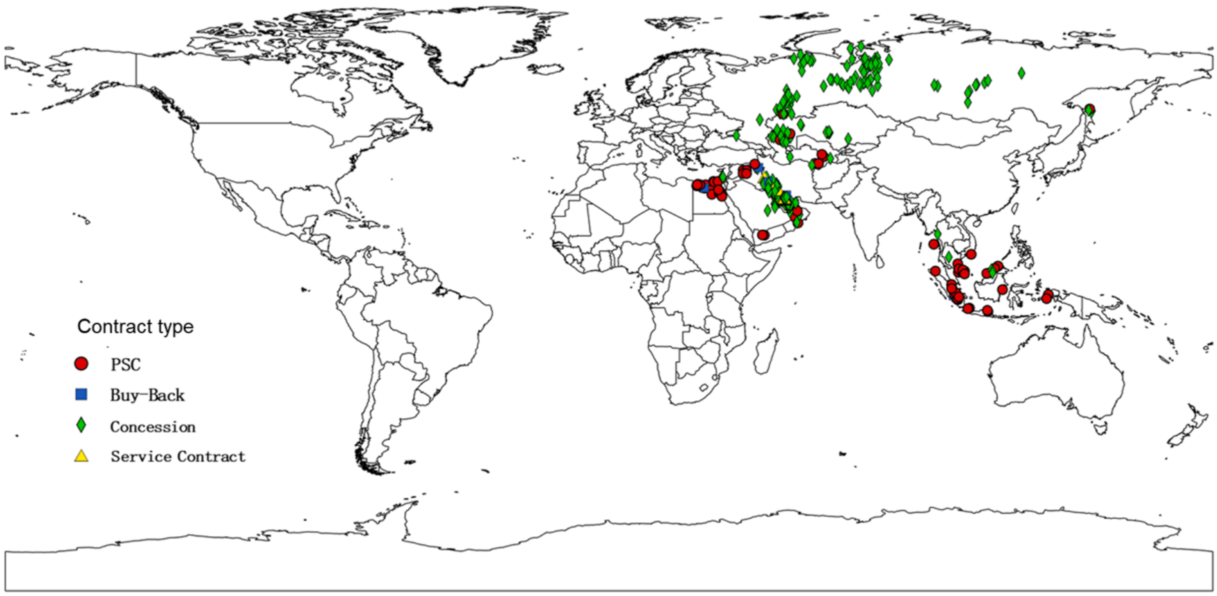

Fig. 3. The tendered oil projects in the BRI countries.

$$\overline{G}_1^{(mk)} = (G_1^{(mk)} - \min_m G_1^{(mk)})/(\max_m G_1^{(mk)} - \min_m G_1^{(mk)})$$
$$\overline{G}_t^{(mk')} = (G_t^{(mk')} - \min_m G_t^{(mk')})/(\max_m G_t^{(mk')} - \min_m G_t^{(mk')}) \tag{17}$$
$$k \in \{1,3,4..,7\} \cup \{9,10..,12\}, k' \in \{2,8\}, t \in T$$

The total constraint violation ($VC^{(m)}$) is computed based on normalized constraint violations, see equation (18).

$$VC^{(m)} = \overline{G}_1^{(m1)} + \sum_{t\in T}\overline{G}_t^{(m2)} + \sum_{k=3}^{7}\overline{G}_1^{(mk)} + \sum_{t\in T}\overline{G}_t^{(m8)} + \sum_{k=9}^{12}\overline{G}_1^{(mk)} \tag{18}$$

In addition, due to stochastic characteristics of the algorithm, the results from different runs may have small changes. Inspired by Yu, Zheng, Gao, and Yang (2017), the NSGA-II algorithm has been independently run for several times, and the best pareto frontier is selected from all runs based on the criteria of Center Distance (CD) and Standard Deviation (SD).

CD is an indicator applied to test the convergence of the pareto frontier, and it is calculated by equation (19). The pareto frontier will have a better convergence when the CD value is smaller, and it reaches ideal state if the CD's value is 0.

$$CD = \|GC - O\| \tag{19}$$

SD is an indicator used to test the uniformity of the pareto frontier. It is calculated using the Euclidean distance between solutions in the objective function space, see equation (20). A smaller SD value indicates a better distribution of the frontier. Moreover, all the solutions in the Pareto solution set are uniformly distributed if SD = 0.

$$SD = \sqrt{1/M \cdot \sum_{m\in M}(\overline{ds} - ds_m)^2} \tag{20}$$

3.3. TOPSIS algorithm

Since the pareto frontier obtained from NSGA-II contains a large number of optimal solutions, it is difficult for the investors to identify the preferred solutions (Lin & Yeh, 2012). To put the optimization results into real applications, the TOPSIS, introduced by Hwang and Yoon (1981), is employed to select the best compromise portfolio as the final investment decisions. The selection procedure is described as below.

Step 1: The objective function values (f_{ml}) are normalized according to equation (21). $M$is the total portfolio numbers in the pareto frontier obtained from NSGA-II, $f_{ml}$is the lth objective function value of the portfolio$k$.

$$z_{ml} = f_{ml}\Big/\sqrt{\sum_{m=1}^{M} f_{ml}^2}, \quad m = 1,...,M; l = 1,...,3 \tag{21}$$

Step 2: Since the investors have different preferences regarding the three objective functions in the portfolio selections, a matrix of weighted objective function values is established based on equation (22).

$$h_{ml} = \omega_l \cdot z_{ml}, \quad m = 1,2...,M; l = 1,2,3 \tag{22}$$

Step 3: The objective functions of overseas oil investment can be classified into two categories, one is called cost indicators whose performances are better if their values are smaller, the other one is called benefit indicators whose performances are better if their values are bigger. According to this classification, the positive ideal investment portfolio (h^*) and the negative ideal investment portfolio (h^0) are calculated using equation (23) and (24).

$$h_m^* = \begin{cases} \max h_{ml} & \text{if } l \text{ is a benefit indicator} \\ \min h_{ml} & \text{if } l \text{ is a cost indicator} \end{cases} \quad l = 1,...,3 \tag{23}$$

$$h_m^0 = \begin{cases} \max h_{ml} & \text{if } l \text{ is a cost indicator} \\ \min h_{ml} & \text{if } l \text{ is a benefit indicator} \end{cases} \quad l = 1,...,3 \tag{24}$$

Step 4: The best compromise solution is closest to h^* and farthest from h^0 from the pareto frontier set. Moreover, the dirichlet distance is used to measure the distances between different investment portfolios, see equation (25) and (26). $d_k^*$is the dirichlet distance of every portfolio from the positive ideal solution, while d_k^0 is the dirichlet distance of every portfolio from the negative ideal solution.

$$d_m^* = \sqrt{\sum_{l=1}^{3}(h_{ml} - h_m^*)^2} \tag{25}$$

$$d_m^0 = \sqrt{\sum_{l=1}^{3}(h_{ml} - h_m^0)^2} \tag{26}$$

Step 5: A competitiveness index (PR_k^*) is calculated to rank all the investment portfolios in the pareto frontier, see equation (27). Moreover, the portfolio with the biggest index values is selected as the final

Table 2
Statistical of major oil project parameters.

Parameters	Units	Mean	Min.	Max	Std. Dev.
NPV_i	Million $	1657.89	0.80	9238.76	1862.71
TQ_i	Million barrels	371.83	4.34	1035.29	301.05
R_i	/	32.33	14.65	55.24	6.47
OR_i	Million barrels	586.02	5.65	1782.71	442.35
I_i	Million $	1011.79	22.77	8323.36	1119.15
C_i	Million $	172.78	3.16	778.43	138.76
$Q_{i,t}$	Million barrels	12.39	2.35	77.49	12.94
IRR_i	%	29.30%	10.02%	93.91%	19.81%
QA_i	°API	36.64	14.00	85.00	9.05

Note: all the monetary numbers are converted to 2019 terms using the Customer Purchase Index.

investment choice.

$$PR_m^* = d_m^0/(d_m^0 + d_m^*) \tag{27}$$

4. Case study of the B&R overseas oil investment

The Belt and Road Initiative was proposed by the Chinese government in 2015, aiming at enhancing the collaboration between B&R countries and China.[2] Overseas oil investment is one of the most important cooperation areas under BRI, because the Chinese oil dependency has increased sharply during the past two decades, surpassing 70% in 2019. To cope with the serious supply shortage and to create a global, competitive, and integrated oil industry, Chinese oil companies are encouraged by the BRI to invest overseas (Wang & Liu, 2016).

China National Petroleum Corporation (CNPC), a state-owned oil company, plans to conduct overseas oil investment under BRI. The investment planning period spans from 2020 to 2049, but all investment decisions have to be made in 2020. According to the oil bidding market, a total of 292 oil projects located across the four resource regions are available to be invested by the investors.[3] Fig. 3 shows the projects' geographical locations and contract types.

All the project parameters are directly drawn from Wood Mackenzie.[4] This company develops a Global Economic Model (GEM) to conduct asset analysis of every oil project based on several assumptions. For example, the long term crude oil prices in the planning period are assumed to be 60 $/barrel, and the discount rate is chosen as 10%. An asset analysis report can be obtained for every tendered oil project from GEM, which shows the predicted production profiles, capital costs, operational costs, reserves, cash flows and IRRs in the planning horizon. To have a clear grasp of these projects, a summary statistical analysis of the parameters is shown in Table 2. The parameters related to the investor's constraints in the specific context of CNPC's envisaged investment are obtained either from annual reports of CNPC or from consultancy results with CNPC experts. The investment budget is set as 40 billion US dollars for a maximum of 40 overseas oil projects, and the maximum operational cost is chosen as 12 billion US dollars. According to CNPC's historical overseas oil productions, the future annual demand of equity oil is determined as 0.4 billion barrels (2020–2024), 0.6 billion barrels (2025–2044) and 0.4 billion barrels (2045–2049). Moreover, to diversify the project investment, the minimum numbers of invested projects are set as 5 for different resource regions, 2 for different contract types and 5 for the offshore oil projects. The minimum API is set as 22.3, which is the threshold API value between medium crude oil and heavy crude oil. According to the CNPC's profit requirements in overseas oil investment, the minimum IRR of oil projects is chosen as 12% (CNPC, 2018). Two projects (AktobeMunai project and EmbaMunai Area project) belong to the strategic investment set because of the diplomatic cooperation between the Chinese government and the Kazakhstan government.[5] In addition, some countries impose bundled tendering rules, such as Egypt (East Zeit project, Geisum and West Tawila project, and Gemsa South East project) and Russia (Tatneft Field East project and Tatneft Field South project). Some other countries put mutually exclusive constraint on the investment projects, including Saudi Arabia (Wasit project and Arabiyah project) and Qatar (Bunduq project and Dukhan project). The ICRG index in 2018 is used to represent the political risk status of all tendered oil projects.[6] For modeling purposes, the original values have been subtracted from 100 so that projects with bigger index values will have higher risk levels.

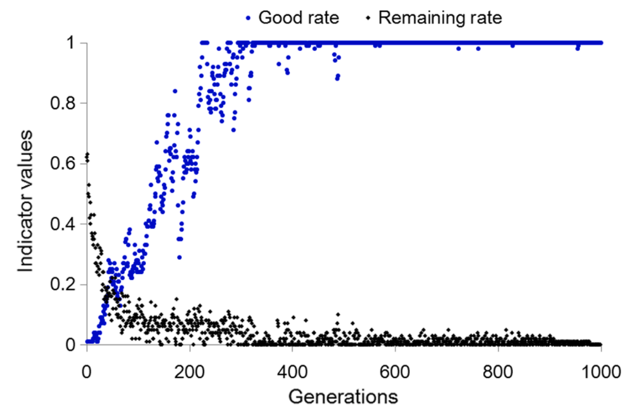

Fig. 4. The solution stability of different generations.

5. Results and analysis

5.1. Pareto frontier of optimal investment portfolios

Based on the established overseas oil investment optimization model (NMBP) and the proposed NSGA-II-TOPSIS solution algorithm, the model has been independently run for ten times with the predetermined parameters of NSGA-II (Pop = 100, Maxgen = 1000, crossover rate = 0.90, mutation rate = 0.01).[7] The pareto frontier with the best CD and SD values from all runs is selected for the final results analysis. Moreover, the result convergences have also been checked using both the remaining rates and good rates of the father generations (see Fig. 4). The results will have better convergence if the remaining rates become smaller or the good rates become higher. It is clear that that the optimization results become stable when the generations surpass 300.

The pareto frontier of the optimal investment portfolio is shown in Fig. 5. Every point in the figure represents an optimal investment portfolio, whose three objective function values are shown in different axes. The average values of the three objective functions are profits (152.32 billion USD), risk (26.09), and reserves (38.88 billion barrels). In all investment portfolios, the profits range between 128.29 billion USD and 170.46 billion USD, the weighted risk index changes from 24.57 to 28.71, and the total reserves from the project portfolios distribute between 33.82 billion barrels to 43.26 billion barrels. The wide ranges of the objective function values of the optimal portfolios clearly demonstrate the challenge in balancing different objectives in the overseas oil investment. In addition, the optimization results of using three single objective functions are also marked in Fig. 5 with different

[2] The country list of B&R countries can be seen from https://www.yidaiyilu.gov.cn/.
[3] https://www.cnpc.com.cn/cnpc/index.shtml.
[4] see https://www.woodmac.com/.
[5] see https://www.yidaiyilu.gov.cn/.
[6] see https://www.prsgroup.com/explore-our-products/international-country-risk-guide/.
[7] The parameter settings are based on Yu et al. (2017).

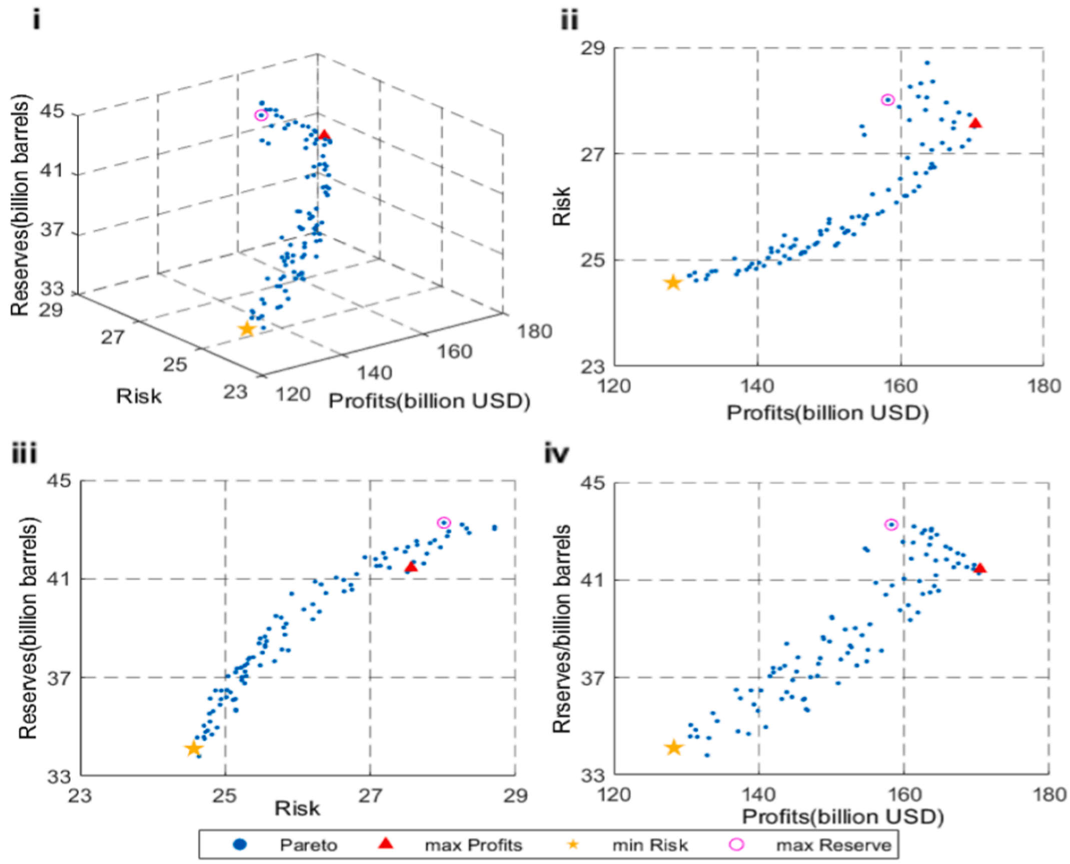

Fig. 5. The Pareto frontier of the overseas oil investment optimization models.

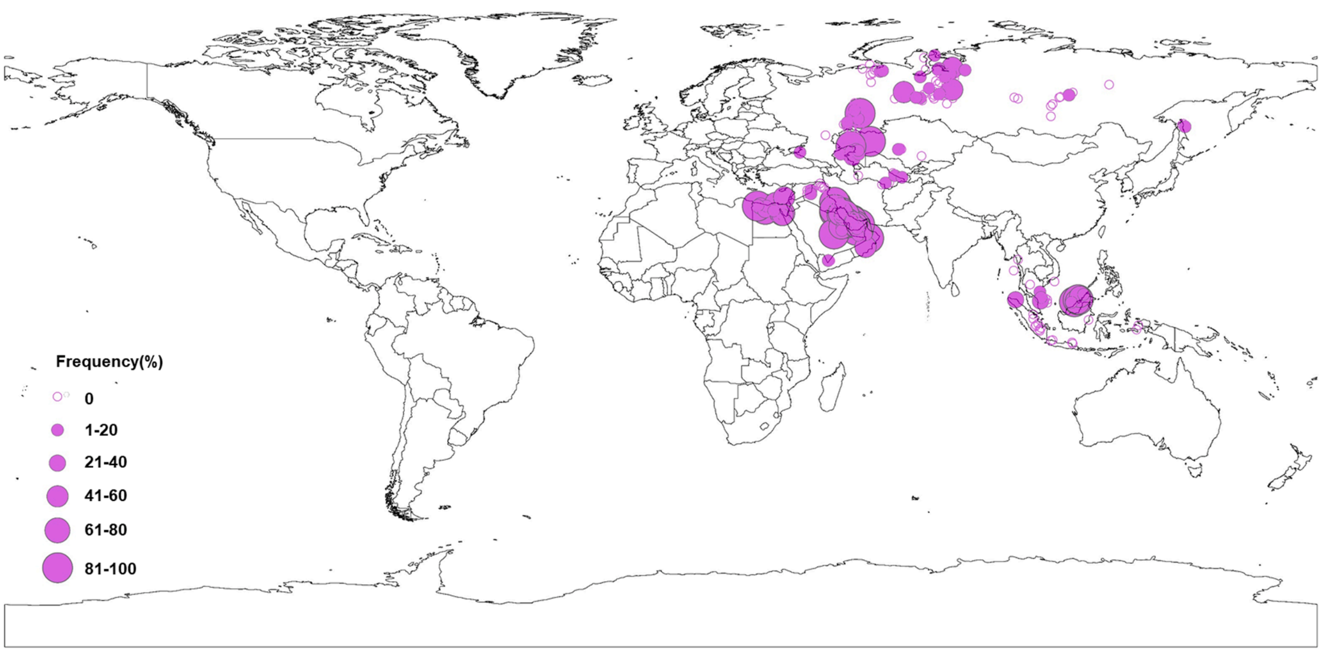

Fig. 6. Frequency of projects appearing in the Pareto frontier.

symbols as reference points. The results comparison highlights the advantages of pareto optimality in solving the multi-objective optimization models and providing decision-makers with much richer information.

To provide guidance for project selection, we have calculated the frequencies of project appearance in the pareto frontier (see Fig. 6). Projects with higher frequency values are more attractive and need more attention in decision-making. Apart from the two strategic investment projects, there are 18 projects that have appearance frequencies of 100%. Most of them are located in the Middle East region. Qatar, United Arab Emirates and Kuwait are the top three countries with the highest

Table 3
Weight sets for different preferences.

Decision making preference	Criterion ranking	Weights sets
A	$f_1 \succ f_2 \succ f_3$	(0.69,0.23,0.08)
B	$f_1 \succ f_3 \succ f_2$	(0.69,0.08,0.23)
C	$f_2 \succ f_1 \succ f_3$	(0.23,0.69,0.08)
D	$f_2 \succ f_3 \succ f_1$	(0.08,0.69,0.23)
E	$f_3 \succ f_1 \succ f_2$	(0.23,0.08,0.69)
F	$f_3 \succ f_2 \succ f_1$	(0.08,0.23,0.69)
G	$f_1 \tilde{} f_2 \tilde{} f_3$	(0.33,0.33,0.33)

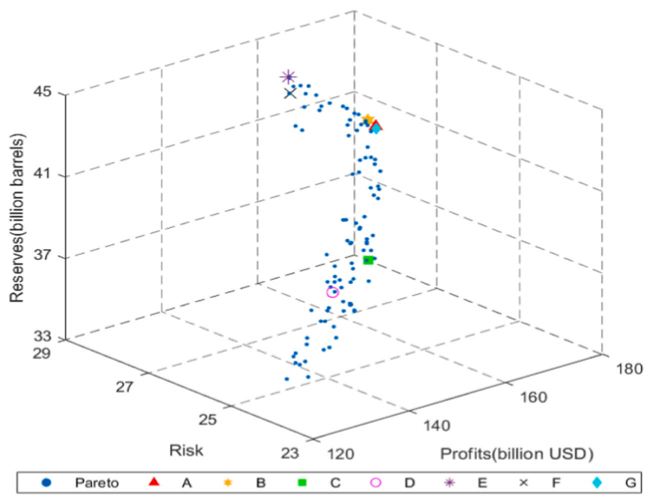

Fig. 7. The final investment portfolio selection under different preferences.

number of invested projects, with every one of them having three projects with appearance frequencies of 100%. However, no project in Thailand and Vietnam has been selected in the pareto frontier, indicating that investing into these two countries would not be a good decision. The frequency information of different projects can help investors make informed decisions efficiently

5.2. Selection and analysis of the final investment portfolio

Based on the obtained pareto frontier, TOPSIS is employed to select the best compromise investment portfolio. Investors may attach different importance to the three objective functions. It is generally easier for them to rank the objective functions rather than to assign exact weights. Therefore, this study takes the rank information as an input, and converts it into weights using the sorting order weight method. The details of converting the rank order information into weights can be seen from Yu et al. (2017). Seven typical rank order combinations of the objective functions are considered in this study, and their calculated weights are shown in Table 3.

The best compromise solutions selected under seven preferences are marked in Fig. 7. This can serve as a useful guiding tool for decision-making in the final portfolio selections. For any decision preferences (A, B, C, D, E, F and G) regarding the three investment objectives, the solution algorithm of NSGA-II returns the final investment decisions. For example, an investor who values profits most and risk least will select portfolio A, while an investor who emphasizes risk most and profits least will choose portfolio F.

Once the final investment portfolio is selected, the projects included in the final investment portfolio are determined. Taken preference G (equal weights) as an example, the included projects are shown in Fig. 8. There are 40 projects included in this particular portfolio, which has profits of 168.62 billion USD, risk of 27.14 and reserve of 41.52 billion barrels, respectively.

We can also obtain the oil production mix of the selected project portfolio in the planning period (see Fig. 9). The total oil production of the investment portfolio experiences three stages: the first one is an increasing production period (2020–2027), the second one is a stable production period (2028–2034) and the third one is a declining production period (2035–2049). In the portfolio, AktobeMunai in Kazakhstan and Messoyakhaneftegaz in Russia contribute most of the total oil production during the planning period. The oil production profiles can be used as important input information for the infrastructure construction planning, oil field operation planning and international oil trading.

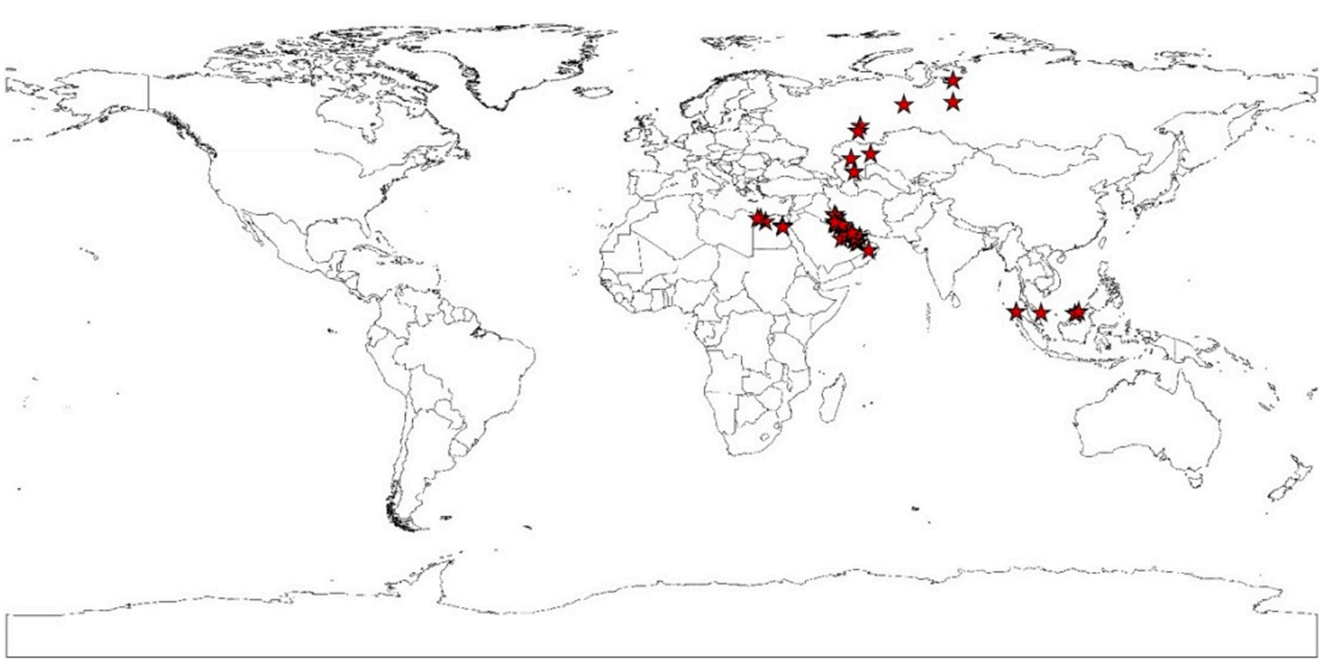

Fig. 8. The spatial distribution of invested projects under the preference G.

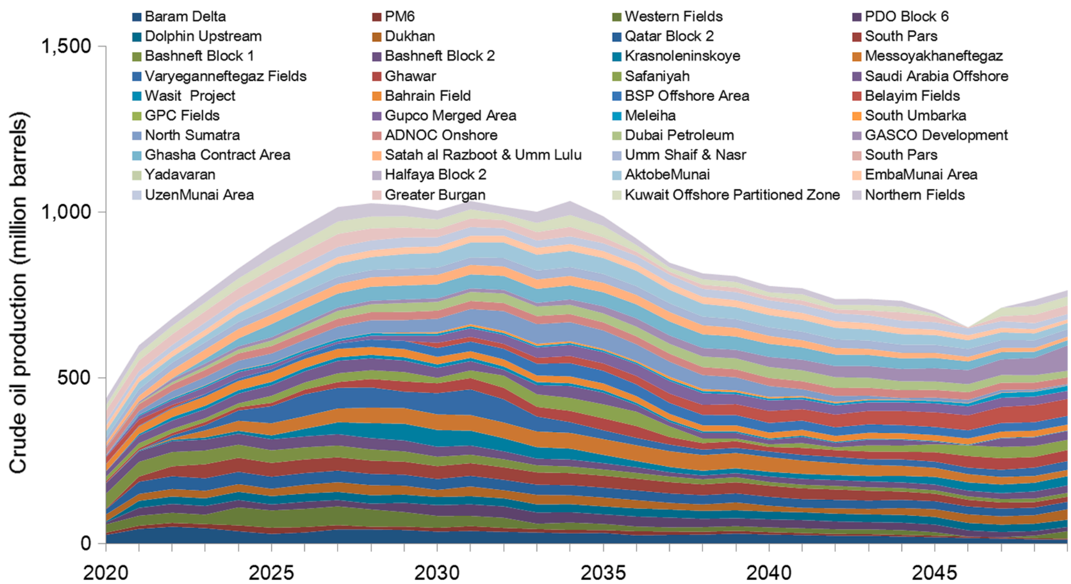

Fig. 9. The oil production mix of the project portfolio in the planning period.

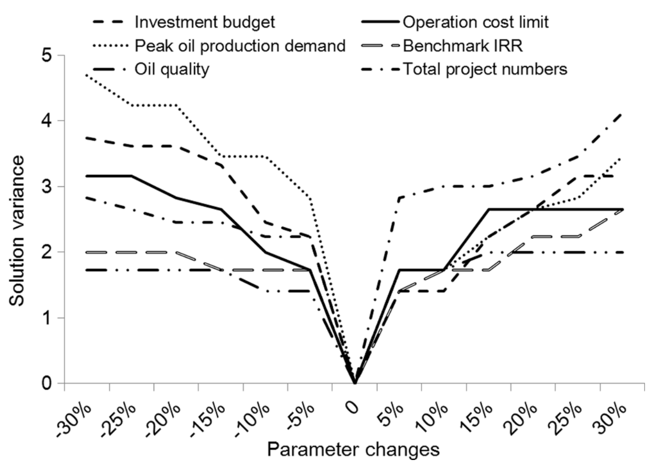

Fig. 10. The sensitivity analysis results.

5.3. Sensitivity analysis

This section conducts a sensitivity analysis to explore the impacts of model parameters on the optimal investment portfolios. In the sensitivity analysis, six major parameters considered are the investment budget, operation cost limit, peak production of equity oil, benchmark internal rate of return, oil quality, and total project number. The module of the solution variance ($|x - x'|$) is chosen as the dependent variables in the sensitivity analysis. $x = [x_1, x_2, ..., x_{292}]$ is the vector of original optimal investment portfolio under the preference G and $x' = [x'_1, x'_2, ..., x'_{292}]$ is the vector of optimal investment portfolio under the changed parameters. All the parameters are changed by -30% to $+30\%$, with a step change of 5%.

As shown in Fig. 10, the final investment portfolio will change if the parameter changes exceed 5%. The final investment portfolio is found to be most sensitive to the increase of total project numbers or the reduction of peak oil production demand, but least sensitive to the lower limit of the oil quality. With these sensitivity analysis results, the investors could establish monitoring mechanism for key parameters, so as to make timely response to the changing environment and parameters.

6. Conclusions

Portfolio choice is a first step in making overseas oil investments and affects the investment success greatly. To advance methodological approach in supporting the investment decisions, this study develops a NMBP model to optimize the investment portfolios. The model considers three competing objectives faced by the investors, including maximization of profits, minimization of risk and maximization of oil reserves. As a salient feature, the political risks of different oil projects are quantitatively introduced to the model by using the ICRG index. The model also incorporates many unique characteristics of overseas oil investments, such as the investment diversification constraint, special bidding rule constraint, oil quality constraint and strategic investment constraint. These improvements enable the model to be better placed to assist decision-making in complex real-world applications than models simply using the traditional mean-variance framework. The model is solvable using an algorithm integrating NSGA-II and TOPSIS, with the former generating a set of pareto optimal solutions and the latter selecting the best compromise solution based on the investor's preferences. China's overseas oil investment in the B&R countries is taken as a case study to demonstrate the function of the established model and algorithm framework.

Potential extensions can be made to improve the proposed model and the algorithm for greater capacity in wider applications. Firstly, since the annual productions of oil projects are directly drawn from asset analysis reports, they are set as parameters rather than decision variables in the optimization model. Therefore, a combined optimization of the portfolio choices and production profiles can be explored in the future. Secondly, the performance of the NSGA-II-TOPSIS algorithm could be compared with other algorithms with respect to solution time and result robustness. This can identify aspects for improvement and also provide valuable reference for algorithm selection in future studies.

CRediT authorship contribution statement

Hao Chen: Conceptualization, Methodology, Writing - original draft. **Xi-Yu Li:** Software. **Xin-Ru Lu:** Data curation. **Ni Sheng:** Writing - review & editing. **Wei Zhou:** Writing - review & editing. **Hao-Peng Geng:** Visualization. **Shiwei Yu:** . **:** Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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