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A Bi-Objective Optimization of Portfolio Risk Response Strategies in Oil and Gas Projects

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Abstract
Risk management and control of project risks have been the intrinsic characteristics of high-rise oil and gas projects in a changing of engineer-procure-construct (EPC) projects. In this research, a novel bi-objective optimization model for the best mixture of projects is proposed. The first objective focuses on maximizing profits and efficiency of risk responses, and the second objective aims at minimizing project direct cost including machinery, human, and material costs to implement proper risk responses over a planning horizon under uncertainty. In this model, risks of the projects are controlled by time, quality, and cost constraints, and the most optimum risk response strategies (RRSs) are selected to eliminate or reduce the impacts of the risks. Thus, the combination of optimum projects with the best RRSs can be selected for an organizational portfolio model. As this model is complex and difficult to solve, another novelty of this paper is to propose a novel hybrid metaheuristic as a combination of red deer algorithm (RDA) and particle swarm optimization (PSO) to address the proposed optimization model. Multi-objective assessment metrics are also employed to have a comparison among this hybrid meta-heuristic and its individual ones. Finally, to assess the proposed solution method and the developed model, the empirical result and sensitivity analysis are carried out. Some large-scale high-rise EPC projects and their associated risks are evaluated as our test cases in this study and managerial insights are concluded from the results.

Keywords
Portfolio Risk Management, Risk Response, EPC Projects, Multi-objective Optimization, Hybrid Meta-heuristic, Red Deer Algorithm, Particle Swarm Optimization

1. Introduction and Background

The importance of an appropriate selection of one project due to the combination of the selected projects for successful portfolio management is inevitable. Many companies try to implement a group of relevant projects as a portfolio to satisfy their synergy and economize their cost through efficient project management. Furthermore, it is needed to manage the risks of each project through the standard

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risk management process after the creation of the appropriate portfolio. The portfolio has an important role in managing a group of relevant projects so that they bring benefits and values. In the portfolio level, risk management requires a balanced attitude and management judgment exercises in two stages: the first stage is associated with the portfolio creation phase and the second one is allocated to the implementation phase of portfolio projects. We only benefit from the synergy and saving resulted from the portfolios projects management in the case of active risk management. A risk strategy response (RSS) is one of the most important processes of risk management. Therefore, selecting the appropriate projects and managing project risks are simultaneously two appropriate approaches to increase both revenue and profits of project-based organizations. In this paper, the main aim is to choose an optimum portfolio of project investment considering its risk response cost and multi-term planning. Project portfolio selection observes the organization's objectives in a planning horizon without outpacing available resources. Schniederjans & Santhanam (1993), classified the system's objectives and preferences as financial benefits, intangible benefits, availability of resources, and risk level of the project portfolio, so project risk assessment was a key element in their study (Ahmad et al., 2018)

Here, an overview on the recent studies in this research area is done. For example, Badri et al. (2001), presented a binary goal programming model for the project selection of an information system. Wei & Chang (2011), presented a portfolio choice model based on enterprise strategy considering customer's resource and capability, project performance and project delivery, and project risk constraints. Project risks are categorized into three types: market risk, technical risk, financial risk. In any aspect of a project, risk can emerge. The nature of risk is uncertainty. For each project, risks should be identified and analyzed, and to cope with these risks, proper RRSs must be employed (Zou et al., 2007; Tang et al., 2007; Mousavi et al., 2011). Tang et al. (2007), developed a new solution method to the lean 6-sigma portfolio management as a binary quadratic programming problem. Muriana & Vizzini (2017), presented a certain method to determine the risk of the Work Progress Status for assessing and preventing project risk.

On the other hand, Rahimi et al. (2018), proposed a mathematical model, in which different risks are considered for activities so that different responses can be selected for each risk. Also, the risk responses are not considered as independent, and responses are associated with each other. Indeed, choosing the responses, which overlap each other, can affect their results, time, cost, and quality of the project. The objective function used different evaluation criteria and tried to choose the optimum responses, which maximizes these evaluation criteria. Ben-David & Raz (2001), considered the cost of implementing strategies and incorporated them into an RRS selection problem. Ben-David et al. (2002), extended their previous work by providing a mathematical model that facilitates computer implementation of the model. Because of the risk abatement actions, a selection problem is a complex one. Therefore, they proposed a branch-and-bound algorithm and two heuristic algorithms (Khodemani-Yazdi et al., 2019; Roshan et al., 2019). Zhang & Fan (2014), integrated all three key elements in project management (i.e., project expenditure, project planning horizon, and project quality). They proposed a new efficient solution for the mathematical model of the RRS.

Reviewing the aforementioned discussions and literature, we understand that there are gaps in (1) selecting the best projects portfolio that the effect of risk in selected projects is controlled (Zhang & Fan, 2014), and (2) selecting projects to check the balance between the total cost of the selected projects and the profit of the selected projects, and all the predicted risk response effects. Furthermore, some of the parameters in the real-world are uncertain and can cause a high degree of uncertainty on a designed network (Zhalechian et al., 2017).

The optimization of RSS is complex and difficult. This motivated several recent studies to contribute novel intelligent-based optimization algorithms to address the proposed problem. Another significant gap among the literature works is that most of the recent works tried to improve the current optimization algorithms or to develop new ones (Zhalechian et al., 2017; Khalilzadeh et al., 2020; Fathollahi-Fard et al., 2020a). This paper applies a recent nature-inspired meta-heuristic as the red deer algorithm (RDA) (Fathollahi-Fard et al., 2020a). In addition, a novel hybrid meta-heuristic as a combination of the RDA and the particle swarm optimization algorithm (PSO) (Kennedy & Eberhart, 1995) to solve the proposed multi-objective optimization model by Pareto-based metrics.

To overcome and to fulfill these gaps, for the first time, we develop an optimization model for selecting the best projects and control risks of each selected projects under uncertainty. In this paper, we investigate the trade-off between the total cost of the selected projects including all three types of resources (e.g., human, machine, raw materials) and implanting proper risk responses-and the net profit of the selected projects, and all the approximated risk response effects. It goes without saying that this problem is complex and high-efficient optimization algorithms are needed. The important items which this paper contributes are as follows:

- Presenting a new two-objective binary optimization model to choose an optimum portfolio and control risks of the selected projects.
- Introducing a new objective function for selecting projects with the maximum net profit and all the estimated risk response effects for each project.
- Developing a new multi-period, multi-project, and multi-resource model to control risks of the selected projects.
- Offering a new hybrid meta-heuristic combining RDA and PSO to solve the proposed bi-objective optimization model.

The rest of this paper is organized as follows: Section 2 establishes a bi-objective optimization model for the proposed RSS. Solution algorithm as our novel hybrid RDA and PSO is proposed in Section 3. The computational results and extensive analyses are provided in Section 4. Managerial implications and practical solutions are discussed in Section 5. Finally, the conclusion of this research and future remarks are drawn in Section 6.

2. Problem Description

We present a new model to select an optimum project portfolio tacking into account many constraints in the multi-period planning horizon. Also, this model can be used to select the RRSs. The portfolio selection problem of the project RRSs is combined with four basic concepts (i.e., project opportunity, work breakdown structure, risk event, and risk responses) as well as three key elements (i.e., schedule, quality, and cost) are considered in these concepts. These concepts are described as project scope, work breakdown structure, risk event, risk response. There is a strategy to respond r risk events. On the other hand, N project should be evaluated with their risk responses' effects to select an optimum portfolio. The optimal portfolio will be top j projects. All parameters of the mathematical model change dynamically. In this model, an optimum portfolio is selected considering its risk response expenditure. The most enticing RRSs can be acquired by solving the mathematical model. Figure 1 depicts the process of portfolio RRSs.

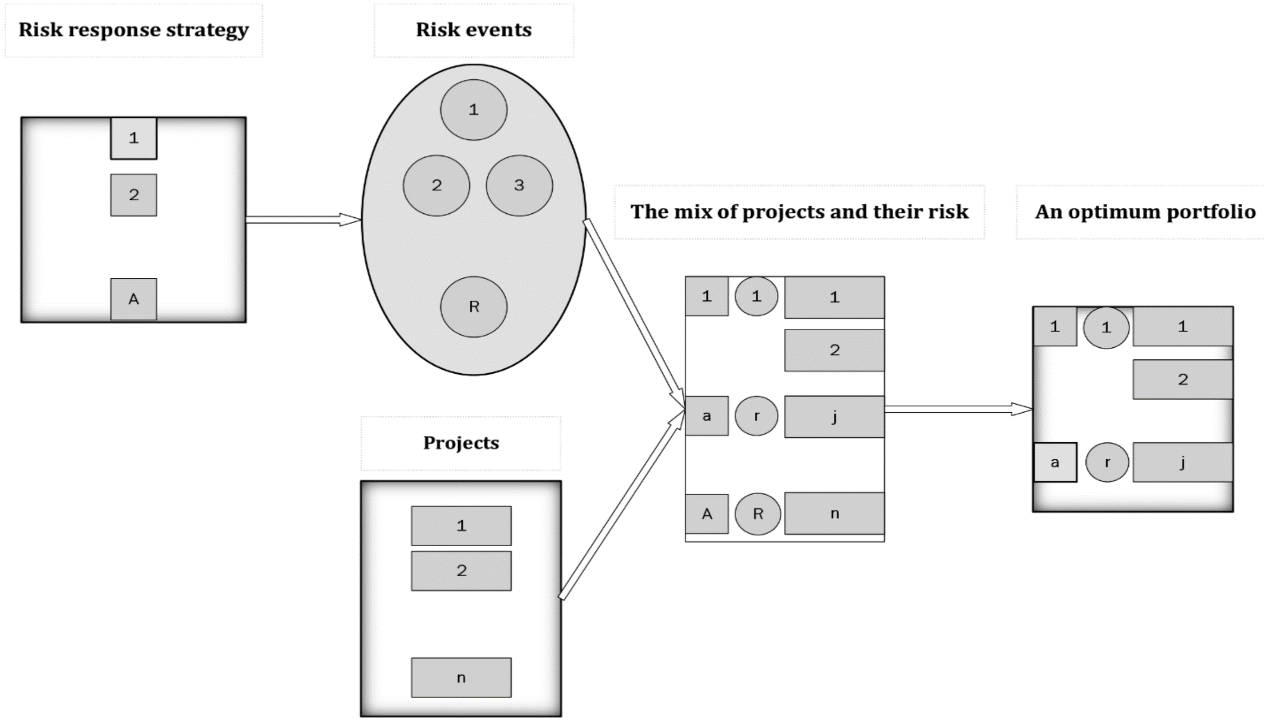


Fig. 1. Process of portfolio RRS

Here, we provide the notations as follows:

Indices:

j	Index of projects $j = 1,2, \dots, n$).
i	Index o human resources (HR) ($i = 1,2, \dots, m$).
k	Index of machinery ($k = 1,2, \dots, s$).
O	Index of material ($O = 1,2, \dots, z$).
t	Index of time period ($t = 1,2, \dots, T$).
w	Index of work packages ($w = 1,2, \dots, W$).
r	Index of risk events (RE) ($r = 1,2, \dots, R$).
a	Index of candidate RRSs ($a = 1,2, \dots, A$).

Parameters:

H_{it}	Max accessible HR i in time t (person-hours).
h_{ij}	Demand of HR i in j (person-hours).
M_{kt}	Max available machine-hour k in time t.
m_{kj}	Demand of machine-hour k in j.
R_{ot}	Max accessible material o in time t.
r_{oj}	Demand of material o in j.
B_{jt}	Maximum available project budget for j in period t.
C_{it}	Hourly cost of HR i in period t.
C_{kt}	Hourly cost of machine k in time t.
C_{ot}	Unit cost of material o in time t.
W_w	Work packages w.
R_r	Risk response (RR) r.

A_a Candidate RRS a.
C_a Cost of implementing risk response strategy *a*.
p_{jt} Total Net Profit (NP) worth of *j* in time *t*.
I_{jt} RoR for *j* in time *t*.
$MARR_t$ MARR during period *t*.
d_{jt} Period of project *j* in time *t*.

Decision variables:
x_{jt} if project j is chosen for investment in time t, 1; otherwise, 0.
z_{jar} 1 if RRS a is applied for RE r for project j; 0, otherwise.

It should also be mentioned that the definition of parameters of s_{ar}^{w}, $s_r^w, q_{ar}^w, \varepsilon^w, \delta^w, \acute{T}_{max}, Q_{max}, \tilde{e}_{ar}, q_r^w\ \overline{M}, \overleftrightarrow{M}$ can be found in Rahimi et al. (2018). Generally, our model is an extension to the study of Rahimi et al. (2018). The main differnce is an additional objective and our model is establihsed as follows:

$$\text{Max } Z_1 = \sum_{t=1}^{T}\sum_{j=1}^{n} x_{jt} \times p_{jt} + \sum_{j=1}^{n}\sum_{a=1}^{A}\sum_{r=1}^{R} z_{jar} \times e_{ar} \tag{1}$$

$$\text{Min } Z_2 = \sum_{t=1}^{T}\sum_{j=1}^{n} x_{jt} \sum_{i=1}^{m} h_{ij}\ .C_{it} + \sum_{t=1}^{T}\sum_{j=1}^{n} x_{jt} \sum_{k=1}^{s} m_{kj}\ .C_{kt} + \sum_{t=1}^{T}\sum_{j=1}^{n} x_{jt} \sum_{o=1}^{z} r_{oj}\ .C_{ot} + \sum_{j=1}^{n}\sum_{a=1}^{A} C_a \max_r z_{jar} \tag{2}$$

s.t.

$$\sum_{t=1}^{T} x_{jt} \le 1 \qquad ;\ \forall j \tag{3}$$

$$\sum_{t=1}^{T} (t + d_{jt})\ .x_{jt} \le T + 1 + T_{max} \qquad ;\ \forall j \tag{4}$$

$$\sum_{j=1}^{n} h_{ij} x_{jt} \le H_{it} \qquad ;\ \forall i, t \tag{5}$$

$$\sum_{j=1}^{n} m_{kj} x_{jt} \le M_{kt} \qquad ;\ \forall k, t \tag{6}$$

$$\sum_{j=1}^{n} r_{oj} x_{jt} \le R_{ot} \qquad ;\ \forall O, t \tag{7}$$

$$\left(\sum_{i=1}^{m} h_{ij}\ .C_{it} + \sum_{k=1}^{s} m_{kj}\ .C_{kt} + \sum_{o=1}^{z} r_{oj}\ .C_{ot}\right) \times x_{jt} < p_{jt}\ , \qquad j = 1,2,\dots,n\ \ ;\ \forall t \tag{8}$$

$$\sum_{j=1}^{n}\sum_{a=1}^{A} \mathrm{C}_a \max_r z_{jar} + \left[\sum_{i=1}^{m} h_{ij}\ \mathrm{C}_{it} + \sum_{k=1}^{s} m_{kj}\ \mathrm{C}_{kt} + \sum_{o=1}^{z} \mathrm{C}_{ot}\ r_{oj}\right] \times x_{jt} \le \mathrm{B}_{jt} \qquad ;\ \forall r, j, t \tag{9}$$

$$\sum_{r=1}^{R} s_r^w - \sum_{r=1}^{R}\sum_{a=1}^{A} \left(s_{ar}^w z_{jar}\right) \le \varepsilon^w \qquad ;\ \forall\ j, w \tag{10}$$

$$\sum_{r=1}^{R} q_r^w - \sum_{r=1}^{R}\sum_{a=1}^{A}\left(q_{ar}^w z_{jar}\right) \leq \delta^w \quad ; \forall j, w \tag{11}$$

$$\sum_{r=1}^{R} s_r^W - \sum_{r=1}^{R}\sum_{a=1}^{A}\left(s_{ar}^W z_{jar}\right) \leq \acute{T}_{max} \quad ; j = n \tag{12}$$

$$\sum_{r=1}^{R} q_r^W - \sum_{r=1}^{R}\sum_{a=1}^{A}\left(q_{ar}^W z_{jar}\right) \leq \quad Q_{max} \quad ; j = n \tag{13}$$

$$\sum_{j=1}^{n} x_{jt} \,.\left(MARR_t - I_{jt}\right) \leq 0 \quad ; \forall t \tag{14}$$

$$\sum_{j=1}^{n} x_{jt} \geq 0 \quad ; \forall t \tag{15}$$

$$z_{jar} + z_{j\acute{a}\acute{r}} \leq 1 \quad (A_a, A_{\acute{a}}) \in \overleftrightarrow{M} \;\; ; \forall j, a, \acute{a}, r, \acute{r} \tag{16}$$

$$z_{jar} + z_{j\acute{a}\acute{r}} = 1 \quad (A_a, A_{\acute{a}}) \in \overleftarrow{M} \;\; ; \forall j, a, \acute{a}, r, \acute{r} \tag{17}$$

$$z_{jar} - z_{j\acute{a}\acute{r}} \leq 0 \quad (A_a, A_{\acute{a}}) \in \overline{M} \;\; ; \forall j, a, \acute{a}, r, \acute{r} \tag{18}$$

$$z_{jar}, z_{j\acute{a}\acute{r}} \in \{0,1\} \quad ; \forall j, a, \acute{a}, r, \acute{r} \tag{19}$$

$$x_{jt} \;\in \{0,1\} \quad ; \forall j, t \tag{20}$$

Objective function value (OFV) (1) maximizes the NP of the selected portfolio and effects on all RRSa for each project of the selected portfolio. Objective function value (2) is minimizing the total cost of the chosen projects consisting of four terms. These terms are the human resource expenditure, the machine resource expenditure, the raw materials resource cost, and implementing the RRSs, respectively.

Constraint (3) ensures that each project selection will happen only one time on the planning horizon. Constraint (4) states that the completion time of each selected project is less than the planning horizon plus the upper bound for project delivery delay. Constraints (5) - (7) define the maximum limits of all three resources. Constraint (5) states that the number of human resources of all types needed for projects during selection cannot exceed the maximum available human resources for all types and all planning terms. Constraint (6) ensures that all machine-hour resources of all types needed for projects during selection do not exceed the maximum available machine-hour resources for all types and all planning terms. Constraint (7) ensures that all raw materials resources of all types needed for projects during selection do not exceed the maximum available raw materials resources of all types and for all planning terms. Constraint (8) certifies that the total cost of each selected project is less than its net profit for all planning terms. Constraint (9) certifies that the total cost of a selected project including human resource expenditure, machine resource expenditure, raw material cost, and implementing the RRSs, is less than its budget for all projects and all planning terms.

Constraint (10) certifies that, in each project, each work packages (except the last one) is completed in the due date, otherwise (if it takes more), it does not affect the schedule of its successors' start times. Constraint (11) ensures that, in each project, each work packages (except the last one) maintain a certain level of quality. Constraint (12) indicates that, in each project, the last work package must be finished in the project deadline. Constraint (13) indicates that in each project, the last work packages must conform to project quality standards. Constraint (14) ensures if a project is selected, it is attractive and that means the internal RoR of the chosen projects should be greater than or equal to the MARR.

Constraint (15) indicates that in each period, projects can be chosen. Constraints (16) – (18) are about strategies. Constraint (16) ensures that strategies A_a, and $A_{\acute{a}}$ prevent each other for each project. Constraint (17) ensures that for each project, only one strategy must be selected if strategies A_a, and $A_{\acute{a}}$ exclude each other. Constraint (18) states that projects cooperate if one strategy is chosen another strategy must be chosen too. Also, in constraint (19) attributes a binary variable for each project. Constraint (20) refers to binary decision variables.

3. Solution Algorithm

The RRS optimization problem is generally classified as an extension to the assignment problems. The assignment or the allocation optimization problems are NP-hard (Schniederjans & Santhanam, 1993; Ahmad et al., 2018; Badri et al., 2001). Therefore, the literature is very rich in using heuristics and meta-heuristics in the area of RRS. Although the PSO algorithm was previously utilized in this research area (Rahimi et al., 2018; Ben-David & Raz, 2001; Zhalechian et al., 2017), there is no study to employ the RDA as a recent nature-inspired algorithm. In addition to this new contribution, this study utilizes a new hybrid meta-heuristic as a combination of RDA and PSO (Deb, 2014; Zhang et al., 2020).

Here, we firstly show the encoding plan to solve the proposed problem. Then, a multi-objective version of RDA which is rarely introduced, is provided and finally, the proposed hybrid meta-heuristic is provided.

3.1. Encoding Plan

Meta-heuristics use a continuous search space. An encoding plan is necessary to show that how a feasible solution can be generated for the fitness evaluation (Khalilzadeh et al., 2020; Fathollahi-Fard et al., 2020a; Chan et al., 2003). A two-stage solution presentation based on random key technique Chan et al. (2003) is considered here. Figure 2 shows the encoding scheme for our decision variables of the developed optimization model.

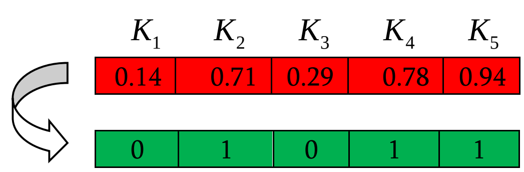


Fig. 2. Selection of risk respones

In this example, assume that we have five possible response and we want to select the optimal one. For each response, a uniform number is selected from the logic of the meta-heuristics. Then, the highest values are selected to be one. The criterion to stop the selection is the budget of the risk response. After each response selected, its cost is calculated to check that the total cost of the responses is lower than the budget.

3.2. Multi-Objective Version of RDA

Evolutionary algorithms are another well-known classification of the metaheuristics. These algorithms are also nature-inspired algorithms. However, from the current to the next generation, only a group of animals who are probably stronger than other ones, will keep and other agents will be removed. As another evolutionary metaheuristic, Fathollahi-Fard et al. (2020a) recently proposed the Red Deer Algorithm (RDA) inspired by an amazing behaviors of males and females in a breeding season.

This algorithm studies the behavior of red deers with regards to roaring, fighting and mating behaviors. These animals are naturally living in British Isles mainly in Scotland. In this regard, the scientists called them as the Scottish Red Deer (*Cervus Elaphus Scoticus*) (Fathollahi-Fard et al., 2020a). In a breeding season, the males which are also known as stags roar loudly and repeatedly to attract the females so-called hinds. Based on this feature of the males, the hinds select their preferable stag and he will create his territory and harem. The harem is a group of hinds and a commander as the head of this group manage and control them. The fighting act is always existed among males. Stags and commanders do a fighting and the winner will achieve the territory and harem. This competition among males is the main activity. The last part of this season is the mating behaviors among males and hinds and as a result, the new red deers will born for the next breeding season. Among all roaring, fighting and mating processes, the evolutionary concept to confirm that only strangest will always keep in nature and this rule is existed among red deers.

Fathollahi-Fard et al. (2020a), modeled these facts as another evolutionary algorithm. They generated the first population of red deers as the random solutions. This population is divided into males and hinds. Then, males roar and based on their power, a group of them will be selected as the commanders and the others are stags. Next, a fight between commanders and stags occurs. After that for each commander, a harem will be generated by some random hinds. The number of hinds in a harem is directly related to the power of the commander. After that the commoner has this ability to mate with a number of his hinds in the harem and a few hinds in another harem. The stags which have not this chance to be a commander can mate with one hind which is closest to him geographically. After the mating, an offspring is created for each mating. Finally, for the next generation, the males will be selected as the best solutions among all available solutions and the hinds will be selected by an evolutionary mechanism like the roulette wheel selection method.

With these features, the authors developed an interesting and successful metaheuristic and called it RDA. According to the best of our knowledge, no paper uses the RDA in the area of the RRS problems. Since our problem is multi-objective optimization, the non-dominated solutions as illustrated in Appendix A must be considered as the outputs of the algorithm. The main differnce of the proposed multi-objective RDA, is the selection of the next generation and the concept of crowding distnace to select the males and hinds. To have a brief illustration of multi-objective RDA, its pseudo-code is available as seen in Fig. 3.

```
Initialize the Red Deers population.
Create the Pareto-based solutions and the non-dominates as the best one.
Form the hinds (N_hind) and male RDs (N_male).
X*=the best solution as one of the non-dominated solutions.
while (t< maximum number of iterations)
   for each male RD
     A local search near his position.
     Update the position if better than the prior ones (it means if it is dominated or not).
   end for
   Update the non-dominated solutions.
    Sort the males and also form the stags and the commanders.
    for each male commander
        Fight between male commander and stag.
        Update the position of male commander and stag.
    end for
   Form harems.
   for each male commander
        Mate male commander with the selected hinds of his harem randomly.
        Select a harem randomly and name it k.
        Mate male commander with some of the selected hinds of the harem.
    end for
   for each stag
        Calculate the distance between the stag and all hinds and select the nearest hind.
        Mate stag with the selected hind.
   end for
   Select the next generation with roulette wheel selection and crowding distance.
   Update the non-dominated solutions.
   Update the X* if there is better solution.
   t=t+1;
end while
return X* and the non-dominated solutions
```

Fig. 3. The pseudo-code of multi-objective RDA

3.3. Proposed Novel Hybrid Meta-Heuristic

Here, the main novelty from the solution algorithm as a novel hybrid of RDA and PSO is introduced. As discussed in Appendix B, each particle in PSO will be updated according to the position of the best and local solutions. We have hybridized this concept to improve the RDA as the main loop of the proposed algorithm and called it as HRDPSOA. In the proposed novel hybrid meta-heuristic, except mating operators, all parts of the algorithm is similar to the RDA. For each mating, we have considered the males as the global solution and the hinds as the local solutions and then updated the offspring. Based on this strategy, we have combined RDA and PSO. The details of this hybrid meta-heuristic are given in Fig. 4 as a pseudo-code.

```
Initialize the Red Deers population.
Create the Pareto-based solutions and the non-dominates as the best one.
Form the hinds (N_hind) and male RDs (N_male).
X*=the best solution as one of the non-dominated solutions.
while (t< maximum number of iterations)
   for each male RD
     A local search near his position.
     Update the position if better than the prior ones (it means if it is dominated or not).
   end for
   Update the non-dominated solutions.
    Sort the males and also form the stags and the commanders.
    for each male commander
       Fight between male commander and stag.
       Update the position of male commander and stag.
    end for
   Form harems.
   for each male commander
       Consider this male as the global solution in PSO
       Consider the hinds as local solutions in PSO
       Mate male commander with the selected hinds of his harem randomly.
       Select a harem randomly and name it k.
       Based on these global and local solutions, mate male commander with some of the selected hinds of the
harem.
    end for
   for each stag
       Calculate the distance between the stag and all hinds and select the nearest hind.
       Consider the male as the global and the hind as the local solution.
       Then, mate stag with the selected hind.
   end for
   Select the next generation with roulette wheel selection and crowding distance.
   Update the non-dominated solutions.
   Update the X* if there is better solution.
   t=t+1;
end while
return X* and the non-dominated solutions
```

Fig. 4. The pseudo-code of hybrid of RDA and PSO (HRDPSOA)

4. Experimental Results

The select Portfolio RRSs proposed in this study is a mixed-integer linear programming model. It worth noting that the general algebraic modeling system (GAMS) software is used to solve the mathematical model and to validate the results of our meta-heuristics including PSO, RDA and HRDPSOA. In this section, a P.G. company (one of the huge companies in the field of oil and gas) in Iran is investigated as a real-case study to validate the performance of the proposed select Portfolio RRSs model.

Two parameters in this method are very critical: relative importance of OFVs (i.e., weight factor) and coefficient of compensation. Details of the distribution functions of the parameters and the size of test problems are listed in Table 1. We also tuned the parameters of the metaheuristics before solving the test problems. The Taguchi experimental desgin emthod was applied and the results of the algorithms' calibration are given in Table 2. Note that due to page limitation, the details of the algorithms' tuning are not reported here.

Table 1. Amount of the parameters by random generation

Parameters	Values		
	First Problem	Second Problem	Third Problem
J	3	3	3
I	20	20	20
K	3	3	3
O	2	2	2
T	5	5	5
W	12	12	12
R	12	12	12
A	8	8	8
p_{jt}	$(2\times10^4, 3.5\times10^4)$	$(4\times10^4, 6\times10^4)$	$(6\times10^4, 9\times10^4)$
e_{ar}	$(5\times10^3, 10^4)$	$(8\times10^3, 2\times10^4)$	$(1.8\times10^4, 5\times10^4)$
C_a	$(10^3, 5\times10^3)$	$(10^4, 2\times10^4)$	$(3\times10^4, 5\times10^4)$

B_{jt}	(5×10^3,1.5×10^4)	(3×10^4,5×10^4)	(5×10^4,7.5×10^4)
C_{it}	(500,700)	(800,1000)	(1500,2000)
C_{kt}	(800,1500)	(2000,3000)	(4000,8000)
C_{ot}	(1000,2000)	(1000,2000)	(1000,2000)

Table 2. Algorithms' tuning

Algorithm	Parameter	Value
PSO	Maximum number of iteration (MaxIt)	500
	Number of Population (nPop)	100
	Rate of weight damper (W)	0.9
	Coefficient of the global solution (C1)	2
	Coefficient of the local solution (C2)	2
RDA	Maximum number of iteration (MaxIt)	500
	Number of Population (nPop)	100
	Percentage of fighting (gamma)	0.8
	Percentage of mating in harms (alpha)	0.6
	Percentage of mating our of harems (betta)	0.6
HRDPSOA	Maximum number of iteration (MaxIt)	500
	Number of Population (nPop)	100
	Coefficient of the global solution (C1)	2
	Coefficient of the local solution (C2)	2
	Percentage of fighting (gamma)	0.8
	Percentage of mating in harms (alpha)	0.7
	Percentage of mating our of harems (betta)	0.5

Based on these test studies, the validation of the algorithms and an extensive comparison are provided. With regards to the exact solver by the GAMS software, the epsilon constraint method is utilized. One objective would be optmized and the second objective is considered as a constraint with an allowable bound (Liu et al., 2020; Koivula et al., 2020; Fathollahi-Fard et al., 2020b). We provided the non-dominated solutions for the first problem as reported in Table 3. These solutions are also depcited in Fig. 4.

Table 3. Non-dominated solutions for the first problem

Epsilon constraint		PSO		RDA		HRDPSOA	
Z_1	Z_2	Z_1	Z_2	Z_1	Z_2	Z_1	Z_2
31040	775	31180.4	785.2	31885.6	808	31978.5	807
32018	804	31570	790.5	32009	812	31993.5	814
32040	820	31862	814.6	32017	837	32009	817
		32015	828	32027	840	32016	821
		32020	833	32035	845	32029	825
						32038	829

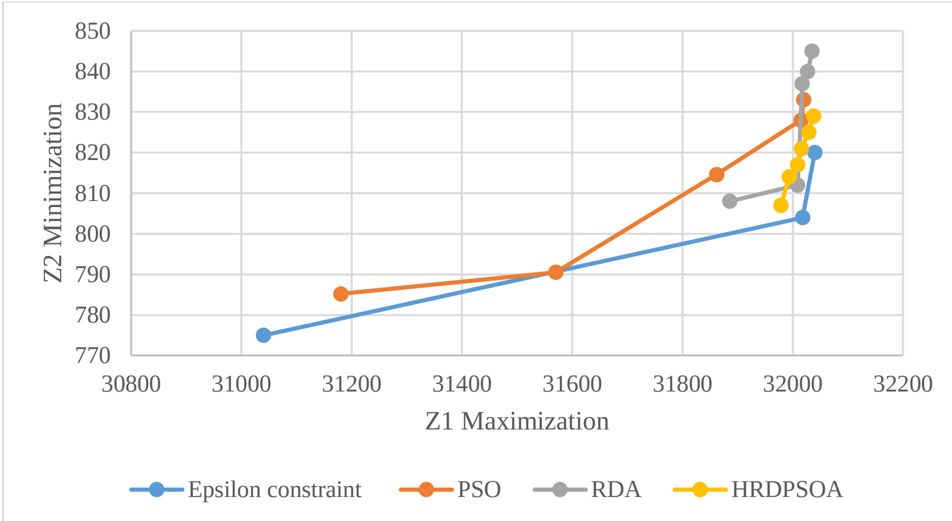


Fig. 4. Non-domianted solutions for the first problem

The results indicated in Table 3 and Fig. 4 confirm that the solutions of HRDPSOA and RDA are highly efficient. They outperform PSO comperhensively. It should be noted that in compariosn with the solutions of the exact solver, the solutions of all meta-heuristics are efficient and validated.

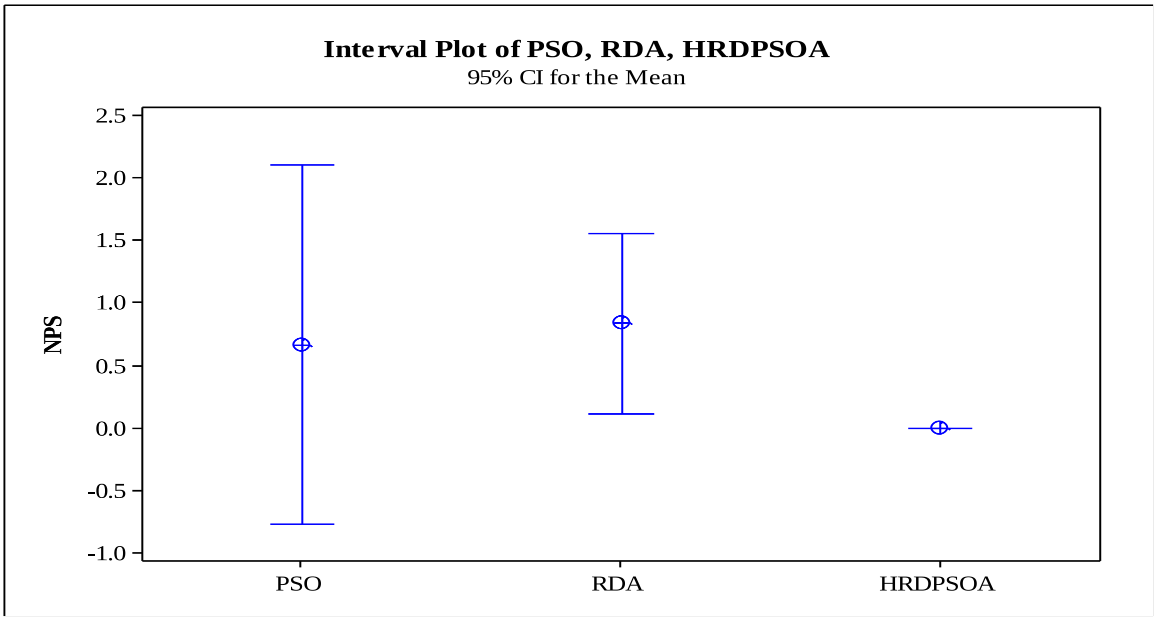
To compare the algorithms, we have utilized four assessment metrics including the number of pareto solutions (NPS), mean ideal distance (MID), spread of non-dominance solution (SNS), and maximum spread (MS). Except MID, for other metrics, a higher value brings a better capability of the algorithm. Table 4 provides the results of the meta-heuristics for the assessment metrics. It should ne noted that all the algorithms are run for 10 times and the average of the results are provided in the reprots. The best values are bold in Table 4.

Table 4. Results of the assessment metrics

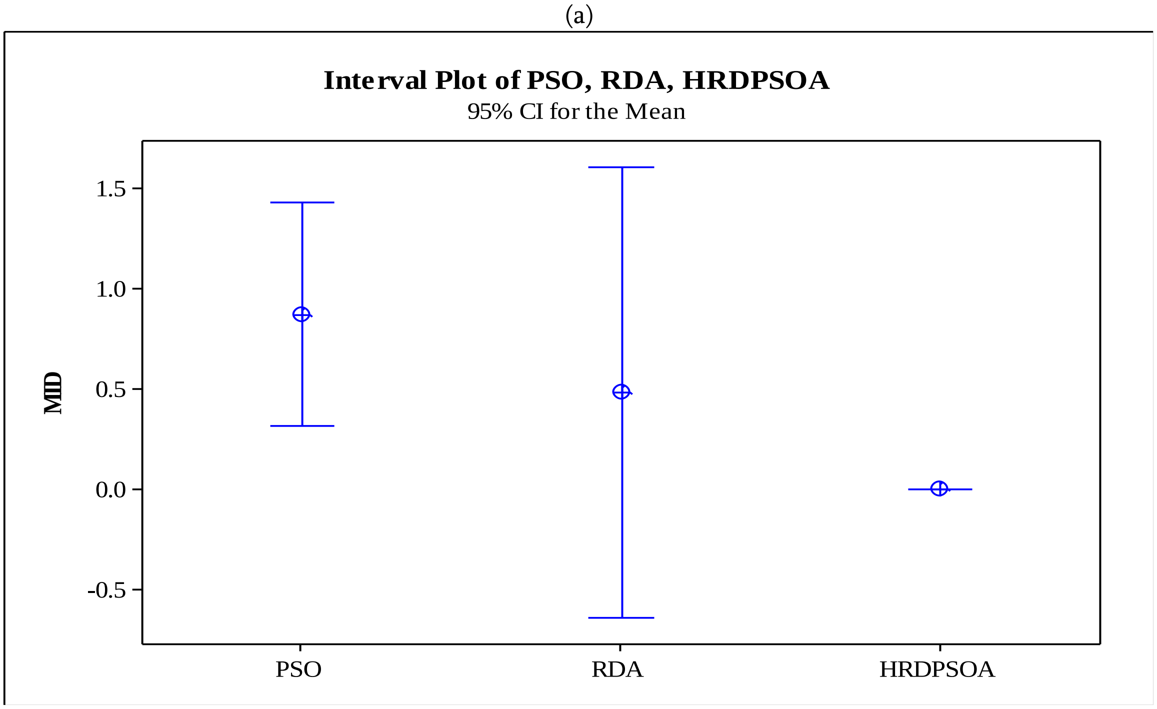
		First Problem	Second Problem	Third Problem
NPS	PSO	5	10	14
	RDA	5	9	16
	HRDPSOA	**6**	**10**	**18**
MID	PSO	2.9316	3.7218	4.0318
	RDA	3.0418	2.9103	3.2864
	HRDPSOA	**2.7581**	**2.6418**	**3.1082**
SNS	PSO	23086	20882	3021
	RDA	21495	18045	**4046**
	HRDPSOA	**26041**	**30166**	3604
MS	PSO	19844	25028	22884
	RDA	18655	20814	24015
	HRDPSOA	**20184**	**30219**	**28918**

The result figuring Table 4 generally confirm that the proposed HRDPSOA is better than PSO and RDA. To show this robustness via statistical tests, we normalize the results of Table 4 and use the interval plot as depicted in Fig. 5.

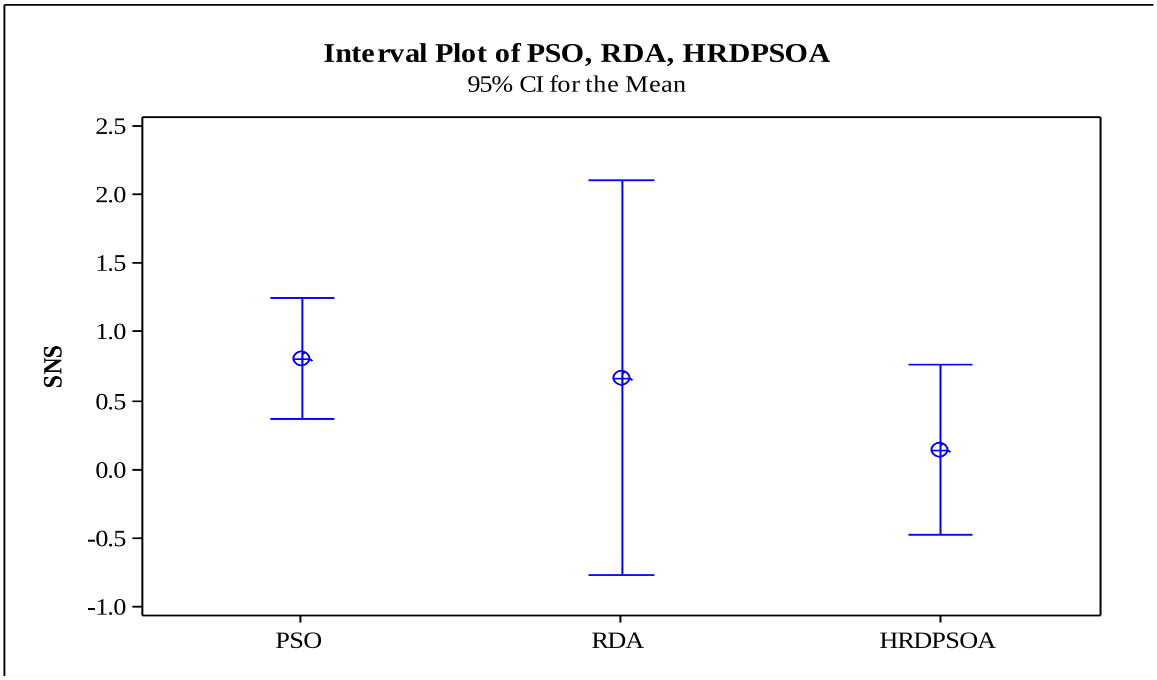
As shown in Fig. 5(a), HRDPSOA is highly better than RDA in the criterion of NPS metric. The RDA is also better than PSO in this metric. Based on the criterion of MID metric (Fig. 5(b)), HRDPSOA outperforms the PSO and consequently, the PSO is slightly better than RDA in this metric. Regarding the SNS metric (Fig. 5(c)), the results are similar to the MID metric. HRDPSOA is signfitcantly better than PSO and RDA. As indicated in Fig. 5(d), the results are similar to the NPS metric. HRDPSOA outperforms the RDA and PSO respectively. It goes without saying that the computational time of the algorithms are very similar and the proposed hybrid meta-heuristic is a little inefficient and based on the quality criterion as given in the assessment metrics, the proposed HRDPSOA is very srtong and efficient in this paper.



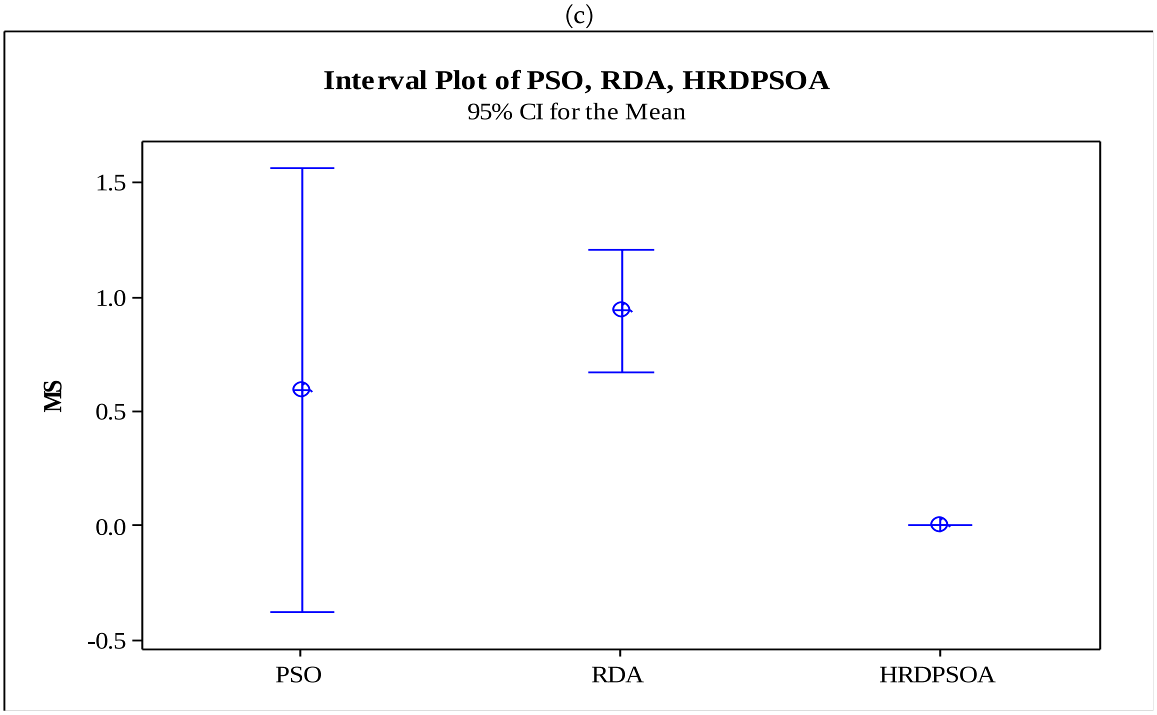
(a)



(b)



(c)



(d)

Fig. 5. Interval plots for NPS(a), MID(b), SNS(c) and MS(d)

To do some sensitivity analyses based on the best algorithm in this study (HRDPSOA), the results on test problems for diverse values of ϑ and φ are shown in Table 5. Note that the average of non-dominated solutions are considered to provide these sensitivity analyses. According to Table 5, the values of objective functions change based on the value of ϑ. The results indicate that satisfaction degrees displaying each objective function change based on the value of ϑ. In this table, the values of satisfaction degree of objective functions (1) and (2) for test problem 2 fluctuate between 0.841 and 0.965, and 0.848 and 0.961, respectively. The results show that by manipulating the value of ϑ, the decision-maker can make trade-offs between two objective functions and select an optimal pair. Generally, increasing the value of ϑ leads to higher allocated weights to acquire a higher lower bound for the satisfaction degree of objectives (λ_0).

Table 5. Results of test problem 1 (β = 0.5).

Problem No.	ϑ	φ	$\mathcal{Z}_1$	$\mu_1(\mathcal{Z})$	$\mathcal{Z}_2$	$\mu_2(\mathcal{Z})$
1	0.6	0.3,0.7	33218.2	0.924	781.08	0.973
	0.6	0.5,0.5	32039.2	0.958	817.20	0.930
	0.6	0.7,0.3	31287.4	0.981	826.98	0.919
	0.4	0.3,0.7	34838.8	0.881	772.35	0.984
	0.4	0.5,0.5	32791.6	0.936	805.93	0.943
	0.4	0.7,0.3	30909.3	0.994	867.57	0.876
2	0.6	0.3,0.7	50448.4	0.892	1317.2	0.911
	0.6	0.5,0.5	48966.2	0.919	1345.3	0.890
	0.6	0.7,0.3	46632.1	0.965	1415.0	0.848
	0.4	0.3,0.7	53507.7	0.841	1248.6	0.961
	0.4	0.5,0.5	51903.1	0.867	1295.8	0.926
	0.4	0.7,0.3	47418.3	0.949	1393.7	0.861
3	0.6	0.3,0.7	70806.1	0.918	2098.6	0.953
	0.6	0.5,0.5	69370.3	0.937	2164.5	0.924
	0.6	0.7,0.3	67427.3	0.964	2171.5	0.921
	0.4	0.3,0.7	71982.2	0.903	2044.9	0.978
	0.4	0.5,0.5	69817.4	0.931	2148.2	0.931
	0.4	0.7,0.3	66598.3	0.976	2229.6	0.897

Table 6. Solution Allocation of RRs for projects 8 and 3

Optimal allocation in project 3	Risks	Work Packages (WP)
RRs 27	R1	WP 1- WP 10
RRs 17	R 5	WP 5- WP 10
RRs 21	R 8	WP 5- WP 10
RRs 10	R 9	WP 3- WP 4
RRs 12	R 12	WP 1, WP 9, WP 10
RRs 7	R 24	WP 2- WP 8
RRs 22	R 25	WP 4- WP 6
RRs 1	R 26	WP 6, WP 7, WP 9
Optimal allocation in project 3	**Risks**	**Work packages**
RRs 27	R 1	WP 1- WP 12
RRs 13	R 2	WP 1, WP 3- WP 10
RRs 14	R 4	WP 2- WP 12
RRs 11	R 7	WP 3- WP 12
RRs 21	R 8	WP 5- WP 12
RRs 10	R 9	WP 5- WP 12
RRs 30	R 10	WP 8, WP 10, WP 11
RRs 16	R 11	WP 3- WP 12

Based on the acquired results and considering the budget and time limitations of the oil and gas projects, the most appropriate strategy for responding to the risk work packages is provided in Table 6. In this test problem project 8 and 3 are selected.

5. Managerial Implications

Large oil and gas companies mainly use the project to carry out their activities as it plays a vital role in Middle East countries like Iran where the risk management of oil and gas projects is a challengeable concern. Due to the limited resources of these companies and the international sanctions in this industry, which can be considered project-based organizations, they have to decide on selecting, stopping projects and allocating resources, and have using portfolio management tools, consequently. Portfolio Risk Management is one of the common knowledge scopes in portfolio management with project portfolio decisions application. The primary purpose of risk management is to protect the organization against damages and to prepare the organization for possible future damage. Therefore, the risks should be met with proper risk responses. Risk management at the portfolio level supports the aforementioned goals in different ways.

Firstly, enables the portfolio manager to compare the risks of single projects in terms of risk feature reduction actions. This comparison allows to make difference between options and the single risk levels are clarified and the results of risk responses actions are reflected and facilitate the transfer of experiences between the projects. Secondly, the comparison of the public risks of the portfolio and its trend according to the life cycle of the project has been revealed. Clarity growth leads to preventing other project risks or increasing focus on risks that are prevalent in most of the projects. Thirdly, risk management reduces uncertainty by providing enough information to make decisions. At last but not least, the results of this paper significantly demonstrate the performance of the proposed hybrid meta-heuristic, HRDPSOA in comparison with its individual PSO and RDA for three classification of test problems and four assessment metrics of the Pareto-based optimization. As a result, estimations are more accurate, reliable, and reduce the chance of surprise and the rate of failures. Therefore, risk management should increase information clarity, detecting and clarifying problems, risk response capacity, and depth of information for decision making.

6. Conclusion and Future Works

In this research, a linear binary programming model was presented to solve a project selection problem and provide RRSs. To solve the model, 10 EPC projects were studied, and net profit, resource, and cost were considered as objective functions. Finally, the optimal allocation of RRSs was determined. Another novelty of this paper was to propose a novel hybrid meta-heuristic for the first time as a combination of RDA and PSO abbreviated as HRDPSOA. All the algorithms were validated by the results of the exact solver in GAMS software based on the epsilon constraint method. The comparison among these algorithms based on the Pareto-based metrics confirm that the proposed hybrid algorithm is strong and efficient. Based on several sensitivity analyses, the results indicated that this model could act as an effective criterion and helped the decision-makers or project managers to increase the desirable impacts of a solution before implementing the project.

Future works are recommended by several additions to the proposed model and more in-depth analyses. For example, incorporating the proposed model with the sustainable development paradigm can create a sustainable RRS optimization problem for the first time. An assessment on the proposed hybrid meta-heuristic with the standard benchmark functions is also interesting for future studies.

References

Ahmad, Z., Thaheem, M. J., & Maqsoom, A. (2018). Building information modeling as a risk transformer: An evolutionary insight into the project uncertainty. *Automation in Construction, 92*(1), 103-119. https://doi.org/10.1016/j.autcon.2018.03.032

Badri, M. A., Davis, D., & Davis, D. (2001). A comprehensive 0–1 goal programming model for project selection. *International journal of Project management, 19*(4), 243-252. https://doi.org/10.1016/S0263-7863(99)00078-2

Ben-David, I., & Raz, T. (2001). An integrated approach for risk response development in project planning. *Journal of the Operational Research Society, 52*(1), 14-25. https://doi.org/10.1057/palgrave.jors.2601029

Ben-David, I., Rabinowitz, G., & Raz, T. (2002). Economic optimization of project risk management efforts. *The Israel Institute for Business Research*.

Chan, H., Perrig, A., & Song, D. (2003). *Random key predistribution schemes for sensor networks.* Paper presented at the 2003 Symposium on Security and Privacy, 2003. 10.1109/SECPRI.2003.1199337

Deb, K. (2014). Multi-objective optimization *Search methodologies* (pp. 403-449): Springer. https: /10.1007/978-1-4614-6940-7_15

Fathollahi-Fard, A. M., Hajiaghaei-Keshteli, M., & Tavakkoli-Moghaddam, R. (2020a). Red deer algorithm (RDA): a new nature-inspired meta-heuristic. *Soft Computing, 24*(1), 1-29. https://doi.org/10.1007/s00500-020-04812-z

Fathollahi-Fard, A. M., Hajiaghaei-Keshteli, M., Tian, G., & Li, Z. (2020b). An adaptive Lagrangian relaxation-based algorithm for a coordinated water supply and wastewater collection network design problem. *Information Sciences, 512*(1), 1335-1359. https://doi.org/10.1016/j.ins.2019.10.062

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of ICNN'95-International Conference on Neural Networks* (Vol. 4, pp. 1942-1948). IEEE.

Khalilzadeh, M., Balafshan, R., & Hafezalkotob, A. (2020). Multi-objective mathematical model based on fuzzy hybrid multi-criteria decision-making and FMEA approach for the risks of oil and gas projects. *Journal of Engineering, Design and Technology, 18*(6), 1997-2016. https://doi.org/10.1108/JEDT-01-2020-0020

Khodemani-Yazdi, M., Tavakkoli-Moghaddam, R., Bashiri, M., & Rahimi, Y. (2019). Solving a new bi-objective hierarchical hub location problem with an M/M/c queuing framework. *Engineering Applications of Artificial Intelligence, 78*(1), 53-70. https://doi.org/10.1016/j.engappai.2018.10.004

Koivula, A., Räsänen, P., Oksanen, A., & Keipi, T. (2020). Risk response over time: political compartmentalization of terrorism risk perception. *Journal of Risk Research*, 1-15. https://doi.org/10.1080/13669877.2020.1750461

Liu, X., Tian, G., Fathollahi-Fard, A. M., & Mojtahedi, M. (2020). Evaluation of ship's green degree using a novel hybrid approach combining group fuzzy entropy and cloud technique for the order of preference by similarity to the ideal solution theory. *Clean Technologies and Environmental Policy, 22*(2), 493-512. https://doi.org/10.1007/s10098-019-01798-7

Mousavi, S., Tavakkoli-Moghaddam, R., Hashemi, H., & Mojtahedi, S. (2011). A novel approach based on non-parametric resampling with interval analysis for large engineering project risks. *Safety science, 49*(10), 1340-1348. https://doi.org/10.1016/j.ssci.2011.05.004

Muriana, C., & Vizzini, G. (2017). Project risk management: A deterministic quantitative technique for assessment and mitigation. *International journal of Project management, 35*(3), 320-340. https://doi.org/10.1016/j.ijproman.2017.01.010

Rahimi, Y., Tavakkoli-Moghaddam, R., Iranmanesh, S. H., & Vaez-Alaei, M. (2018). Hybrid approach to construction project risk management with simultaneous FMEA/ISO 31000/evolutionary algorithms: Empirical optimization study. *Journal of construction engineering and management, 144*(6), 04018043. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001486

Roshan, M., Tavakkoli-Moghaddam, R., & Rahimi, Y. (2019). A two-stage approach to agile pharmaceutical supply chain management with product substitutability in crises. *Computers & Chemical Engineering, 127*(1), 200-217. https://doi.org/10.1016/j.compchemeng.2019.05.014

Schniederjans, M. J., & Santhanam, R. (1993). A multi-objective constrained resource information system project selection method. *European journal of operational research, 70*(2), 244-253. https://doi.org/10.1016/0377-2217(93)90042-L

Tang, W., Qiang, M., Duffield, C. F., Young, D. M., & Lu, Y. (2007). Risk management in the Chinese construction industry. *Journal of construction engineering and management, 133*(12), 944-956. https://doi.org/10.1061/(ASCE)0733-9364(2007)133:12(944)

Wei, C.-C., & Chang, H.-W. (2011). A new approach for selecting portfolio of new product development projects. *Expert Systems with Applications, 38*(1), 429-434. https://doi.org/10.1016/j.eswa.2010.06.081

Zhalechian, M., Tavakkoli-Moghaddam, R., & Rahimi, Y. (2017). A self-adaptive evolutionary algorithm for a fuzzy multi-objective hub location problem: An integration of responsiveness and social responsibility. *Engineering Applications of Artificial Intelligence, 62*(1), 1-16. https://doi.org/10.1016/j.engappai.2017.03.006

Zhang, L., Chen, L., Xia, S., Ge, Y., Wang, C., & Feng, H. (2020). Multi-objective optimization for helium-heated reverse water gas shift reactor by using NSGA-II. *International Journal of Heat and Mass Transfer, 148*(1), 119025. https://doi.org/10.1016/j.ijheatmasstransfer.2019.119025

Zhang, Y., & Fan, Z.-P. (2014). An optimization method for selecting project risk response strategies. *International journal of Project management, 32*(3), 412-422. https://doi.org/10.1016/j.ijproman.2013.06.006

Zou, P. X., Zhang, G., & Wang, J. (2007). Understanding the key risks in construction projects in China. *International journal of Project management, 25*(6), 601-614. https://doi.org/10.1016/j.ijproman.2007.03.001