Research on Priority Rules for the Stochastic Resource Constrained Multi-project Scheduling Problem with New Project Arrival

HaoJie Chen[a], Guofu Ding[a], Jian Zhang[a,□], Shengfeng Qin[b]

[a] *School of Mechanical Engineering, Southwest Jiaotong University, Chengdu 610031, China*

[b] *Department of Design, Northumbria University, Newcastle Upon Tyne NE1 8ST, UK*

Abstract: The resource constrained multi-project scheduling problem (RCMPSP) is a general and classic problem, which is usually considered and solved in a deterministic environment. However, in real project management, there are always some unforeseen factors such as one or more new project arrivals that give rise to intermittent changes in the activity duration (or stochastic duration) of the current project in execution by inserting the new project. This study takes two practical factors in terms of stochastic duration of project activities and new project arrivals waiting for insertion into account of the problem space to form a stochastic resource constrained multi-project scheduling problem with new project arrivals (SRCMPSP-NPA). Based on the benchmark of the PSPLIB (Project Scheduling Problem Library), a new data set is built and 20 priority rules (PRs) are applied to solve the problem and their performances are analyzed. In addition, a heuristic hybrid method is designed for solving the problem timely by dividing the entire scheduling process into multi-state scheduling problems solved by the corresponding rules separately. This approach has been verified by experiments and its performance
is better than that of a single rule in most situations.

Key words: Multi-project scheduling; Priority rule; Stochastic duration; New project arrival; Heuristic hybrid

1 Introduction

RCMPSP has been a very active research field in Project Management over the past ten years (Besikci, Bilge & Ulusoy, 2015; Suresh, Dutta & Jain, 2015; Song et al, 2018). In a deterministic environment, the solution of RCMPSP forms baseline scheduling by optimizing one or several objective functions. However, during anexecuting process of a baseline scheduling, some dynamic factors can disturb pre-designed plans and vary the planned activity duration. For example, in a typical production process, both machines and human workers are working together, due to skill improvement of human workers or executive failure of a machine, the activity duration will be shorter or longer than originally planned. The initial baseline scheduling needs revised accordingly to accommodate the uncertain changes. In addition, to support mass customization in production, changes in customer demand or the emergence of new customers will lead to the changes in product orders irregularly and intermittently, which in turn results in new project arrivals and new project insertions request depending on their business priority. Due to resource constraints, when two dynamic factors occur together in terms of stochastic duration and new project arrival , they will have a greater impact on the baseline scheduling, so this kind of dynamic resource constrained multi-project scheduling problem, needs to model them in the problem space explicitly for easily understanding and describing the problem and solve the new problem formation accordingly.

For coping with this problem, the exact algorithm is not applicable because RCMPSP is a NP-hard problem (Blazewicz, Lenstra & Rinnooy-Kan, 1983), and the meta-heuristic algorithm in approximation approach requires a large number of iterations, which could not respond to the frequent occurrences of dynamic factors timely, especially for a middle- or large-scale scheduling problem. Therefore, using heuristic-based priority rules (PRs) is a suitable choice. For RCMPSP in a deterministic environment, Browning & Yassine (2010) summarizes and analyzes the performance of 20 PRs. However, a further study is required to determine whether these PRs can be used to handle the RCMPSP with new project arrival coupled with stochastic duration in real time (or dynamic RCMPSP), and what PRs are best suitable for solving this dynamic problem.

This paper adequately considered both stochastic duration and new project arrival together in dynamic RCMPSP with a systematic study. Our research contributions are threefold. (1) we propose a new problem formation named SRCMPSP-NPA, a stochastic resource constrained multi-project scheduling problem with new project arrival, and build its mathematical model, (2) based on the schedule generation scheme and the PSPLIB benchmark, we evaluate the performances of 20 PRs used to solve the SRCMPSP-NPA, and (3) we study a heuristic hybrid method for effectively solving the problem bydividing the scheduling of the portfolio into different states according to the completion condition of the portfolio and choosing the corresponding rules in different states.

The remainder of the paper is organized as follows. Section 2 reviews related work and Section 3 introduces the scheduling principle and mathematical model of SRCMPSP-NPA. The generation scheme of the solution, the corresponding PRs and the heuristic blending method are explained in Section 4. Section 5 is mainly an experimental explanation, including the construction of data sets, analysis of experimental results and performance comparison. Section 6 summarizes and concludes this paper and gives the new perspectives of future research.

2 Related work

The resource-constrained project scheduling problem (RCPSP) has been receiving widespread attentions during the time being proposed and is proved to be a NP-hard problem. Many extensions and improvements of RCPSP, including models and solutions, have been studied, analyzed and summarized (Özdamar, & Ulusoy, 1995; Herroelen, De Reyck & Demeulemeester, 1998; Brucker et al, 1999). RCMPSP is the most common extension of RCPSP as up to 90% of the cases belong to multi-project management (Payne, 1995). For RCMPSP, there are the two most common strategies, combined solution (Gonçalves, Mendes, & Resende, 2008) and independent solution (Kurtulus, I & Davis, 1982). The former decomposes each project into activities and then combines them into a portfolio (project set) with only one start node and one termination node (usually dummy node). This approach has two drawbacks. On the one hand, it is easy to lose some local information of the project. On the other hand, it should be ensured that the time information of all projects is the same, such as the latest start time and the earliest start time, which is not in line with the actual situation (Kurtulus, 1985). The latter one is independent solution, in which each project has its own start node and end node, also called multi-project solution. Compared to the former, the multi-project solution has higher optimization ability and potential (Herroelen, 2005).

Due to its advantages, the multi-project scheduling strategy has attracted the majority of compelling researchers andmany methods have been developed and improved (Hartmann & Briskorn, 2010) such asexact solution(Patterson ,1984) ,the branch and bound method (Demeulemeester & Herroelen, 1992), the decomposition approach (Deckro et al, 1991; Vercellis, 1994) and the 0-1 planning model (Chen, 1994). However, these methods are only suitable for solving small-scale RCMPSP. For a large-scale RCMPSP problem, heuristic or meta-heuristics are gradually becoming the mainstream method. Heuristic-based PRs, also known as the single-pass and multi-pass method (Hartmann & Kolisch, 2000), are divided into three categories by Kolisch (1996b), which are the activity-based, project-based, and resource-based rules. Activity-based rules are based on the time characteristics of activities, such as the duration or the earliest/latest start/finish time of an activity. Project-based rules add some project information on activity-based rules, while resource-based rules determine priorities depending on the resource demands of the activity or the project. Many classic PRs have gradually being developed, applied and compared by performance analysis (Thomas & Salhi, 1997; Akpan ,2000). These PRs are summarized, investigated and classified by Kurtulus & Davis (1982) and Browning & Yassine (2010) into three categories in a multi-project environment. In addition, some commonly used meta-heuristic algorithms, such as genetic algorithm (Kumanan, Jose & Raja, 2006), particle swarm optimization (Linyi & Yan, 2007) and some local search algorithms (Geiger, 2017) are applied to solve RCMPSP and achieved good results. In order to overcome the shortcomings of the single meta-heuristic algorithm, researchers have developed some hybrid algorithms, and obtained better results from, for instance, combining genetic algorithm with simulated annealing (Chen & Shahandashti ,2009) and mixing genetic algorithm with fuzzy logic (Kim et al, 2005).

Although the above researches have made great breakthroughs in the process of solving problems, they are all in a static or deterministic environment. In the real environment, there are often different dynamic factors, for example, the duration of the activity is earlier or later than expected, new projects are arrived or inserted, resources are scarce during a short period in the execution of the portfolio, etc. In contrast, the dynamic of uncertainty about duration has been studied more and more. Thus, RCPSP develops into a new problem, stochastic resource-constrained project scheduling problem (SRCPSP), and RCMPSP evolves into a stochastic resource-constrained multi-project scheduling problem (SRCMPSP). In the case where the duration of the activity is uncertain, but satisfies a known probability distribution function is studied in detail (Bruni, Beraldi & Guerriero, 2015).

For SRC(M)PSP, many studies have used some meta-heuristic (Fang et al, 2015; Zheng et al, 2017; Nabipoor, Aghaie & Najafi, 2018) or approximate programming (Li & Womer, 2015; Alipouri et al, 2017) algorithms. Obviously, the computational performance of scheduling is more important to timely response to the changes of the environment for this problem, while the meta-heuristic algorithm requires a large number of iterations, which affects the computing time. Therefore, PRs are strongly recommended and suggested (Wang et al, 2017). For the scheduling with PRs, there have been some related studies in recent years. Chen et al (2018) analyzes and summarizes six scheduling policy classes to solve SRCPSP, including resource-based, activity-based, earliest-start, pre-selective, pre-processor and generalized preprocessor policies. Based on this classification, 12 reference PRs and 5 self-designed PRs (prioritized by indicator mathematical expectations) are applied to the PSPLIB benchmark (Kolisch & Sprecher, 1996) in which 5 distributions of activity duration are used for experiment and performance comparison. In this study, the minimum latest finish time (LFT) and the minimum statistical latest start time (SLFT) significantly outperform other direct PRs and simulation-based PRs respectively. In addition, the 5 heuristic algorithms are applied to the same problem, and their performance is inferior to that of LFT and SLFT under more iteration numbers or operations, thus proving the validity of PRs. Zheng et al (2013) constructs a discrete bi-objective decision model based on priority to solve SRCMPSP. Through experimental verification, the three parameters of order strength, resource constraint and uncertainty level have evident impacts on the robustness and makespan of the portfolio. Wang et al (2015) establishes a Markov decision process model to deal with SRCMPSP. First, some effective PRs are used to narrow the solution space, and then dynamic programming is used to optimize the corresponding objective function values. This method shows good result in the experiments. Wang et al (2017) uses the same 20 rules as Browning & Yassine (2010) in SRCMPSP. The new data set based on the RanGen2 strategy (Vanhoucke et al, 2008) is constructed and the performance of solution quality and robustness is analyzed from both the project and portfolio perspectives. In the experiments of this research, the earliest due date first (EDDF) rule is superior to other rules in all aspects, whether the distribution is uniform, exponential or triangular with different parameters.

According to our knowledge so far, there is no literature to consider new project arrivals in the SRCMPSP as it used to consider only the stochastic duration of existing projects. Obviously, new project arrivals cause greater uncertainty on account of limited resources which makes baseline scheduling more difficult to be executed on schedule. How to descript these two dynamic factors in the problem, build the correspond mathematical model and obtain a satisfied solution by an advanced strategy as quickly as possible to response to the rapid changes based on current related work should be researched.

3 Problem Descriptions

3.1 SRCMPSP-NPA Principle

The components and scheduling principles of SRCMPSP-NPA are shown in Fig.1. The whole problem consists of two parts, including the initial scheduling set of projects called the portfolio, and the insertion portfolio that contains all the new arrivals of upcoming projects. At a random time *t*, if the portfolio does not exceed its maximum project capacity, a randomly selected project in the insertion portfolio will be added to the portfolio for scheduling. In this research, only one project is allowed to arrive at a time. The project is a combination of activities with complex precedence relationships, and each activity has two important attributes—required resources and duration. In SRCMPSP-NPA, the duration of each activity is uncertain but obeys a distribution and the pre-emption is not allowed during the scheduling process. There are two special activities in each project, the starting dummy activity and the ending dummy activity, representing the start and end of the entire project respectively, which do not require resources and the duration is zero. The red arrow in Fig.1 expresses the critical path of a project and refers to the theoretical lower bound of its duration. The goal of SRCMPSP-NPA is to minimize (such as cost or makespan) or maximize (resource utilization) one or more objective functions by scheduling the entire portfolio.

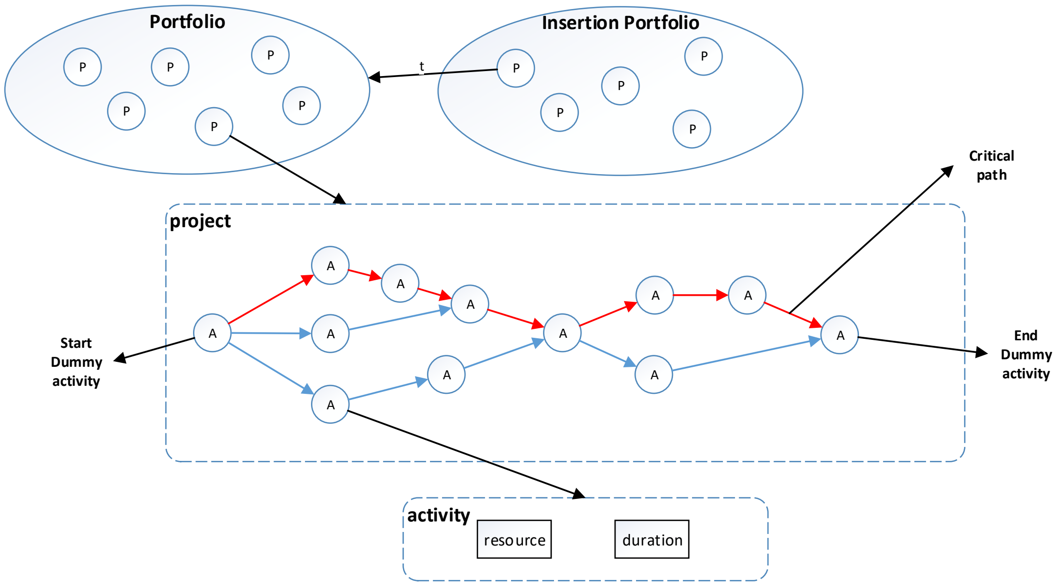

Fig.1 The principle of SRCMPSP-NPA

3.2 Mathematical Model

As described in 2.1 and with reference to Wang et al (2017) and Browning & Yassine (2010), the mathematical model of SRCMPSP-NPA is built and consists of several parts including “notation symbols”, “constraints” and “objective functions”.

Notation symbol

The notations with corresponding meanings required for the mathematical model of SRCMPSP-NPA are shown in Table 1.

Table 1 The notation table

Symbol	Significance
p	the project index
P	the portfolio (initial project set)
P'	the insertion portfolio (insert project set)
a	the activity index
A_p	the activity set in project p
k	the resource index
K_p	the resource type set required in project p
R_k	the maximum unit supply for resource k
r_{pak}	the number of resources k required for activity a in project p
d_{pa}	the duration of activity a in project p
S_{pa}	the successor set of activity a in project p
t_{pa}	the start time of activity a in project p
A_t	the set of all activity that operate at time t

T	the maximum duration for the entire portfolio to complete
NUM_{max}	the maximum project capacity of portfolio
NUM_{start}	the initial project number of the portfolio
x_{pt}	decision variable, if insert project p at time t then it is equal to 1, otherwise equal to 0

Constraint

To construct a feasible schedule in SRCMPSP-NPA, the constraints need to be satisfied as described in Eq.(1) to Eq.(5).

$$t_{pb} - t_{pa} \geq d_{pa} \qquad \forall a \in A_p , \forall b \in S_{pa}, \forall p \in P \ \ or \ P' \tag{1}$$

$$d_{p0} = 0, d_{pA_p} = 0, r_{p0k} = 0, r_{pA_pk} = 0 \qquad \forall k \in K_p, \forall p \in P \ \ or \ P' \tag{2}$$

$$\sum_{\forall p \in P} \sum_{\forall a \in A_t} r_{pak} \leq R_k \qquad \forall k \in K_p, \forall t \in T \tag{3}$$

$$\sum_{\forall p \in P'} \sum_{\forall t \in T} x_{pt} \leq NUM_{\max} - NUM_{start} \tag{4}$$

$$\sum_{\forall p \in P'} x_{pt} = 1 \quad \forall t \in T \tag{5}$$

Constraint 1 indicates the precedence relationships of activities. Constraint 2 refers to the constraint of dummy activity, that is, each dummy activity includes zero duration and does not require any resources. Constraint 3 is a resource constraint, which represents the sum of the resources k required for all activities operating at each time cannot exceed the maximum supply of resources k. Constraint 4 points out that the number of projects scheduled cannot exceed the capacity of the portfolio. Constraint 5 means that only one new project can arrive and be inserted at each time t.

Objective function

Similar to the two above references, this paper also uses the two aspects of project and portfolio to evaluate the solution quality and robustness. Thus, there are 4 objective functions, which are shown in Eq.(6) to Eq.(9), respectively.

$$Q_1 = \frac{1}{|P|} \sum_{\forall p \in P} \frac{AD_p - CP_p}{CP_p} \tag{6}$$

$$Q_2 = \frac{\max_{p \in P} AD_p - \max_{p \in P} CP_p}{\max_{p \in P} CP_p} \tag{7}$$

$$R_1 = \frac{1}{|P|} \sum_{\forall p \in P} \left| \frac{SAD_p - AD_p}{AD_p} \right| \tag{8}$$

$$R_2 = \left| \frac{\max_{p \in P} SAD_p - \max_{p \in P} AD_p}{\max_{p \in P} AD_p} \right| \tag{9}$$

Where CP_p represents the critical path length of project p, AD_p refers to the actual scheduling duration of project p, and SAD_p indicates that the activities in project p satisfying a certain distribution, the average duration of the project under multiple scheduling. Q_1 (project perspective) and Q_2 (portfolio perspective) in the objective function are evaluation indicators to evaluate the scheduling ability of different strategies solving the same problem when the duration of each activity in the project is deterministic. R_1 (project perspective) and R_2 (portfolio perspective) are measured as the deviation between the duration of activity in a deterministic environment and in a stochastic situation by using different strategies, this is, the robustness of different scheduling strategies.

4 Solution Methods

The main research in this paper is about priority rule scheduling. As one of the fastest heuristics, it constructs feasible solutions by means of schedule generation scheme (Rostami, Creemers & Leus, 2018). Therefore, this section firstly introduces the two main approaches of the schedule generation scheme (SGS), the PRs adopted by this paper in Sect.4.2 and the designed heuristic hybrid method in Sect. 4.3.

4.1 Schedule Generation Scheme

To solve deterministic RCMPSP or SRCMPSP-NPA with most heuristics, the SGS should be chosen at first (Kolisch, 1996a; Chen et al, 2018). The two main types of SGS are proposed by Kelley (1963), including parallel SGS and serial SGS. The former is in the form of time increments while the latter is activity increments. This is, when the parallel SGS is used, it is an iteration of decision points. At each decision point, if no resource conflicts occur, each eligible activity is selected from the priority order list. An activity is eligible means that it is not scheduled and its predecessors have all been completed. In this way, the priority of the activity can be recalculated in the scheduling process if it is necessary. The serial SGS calculates the activity priorities and starts the highest priority activity sequentially as early as possible. The generation of a complete schedule requires N iterations, where N is the total activity number in the entire portfolio. In SRCMPSP-NPA, parallel SGS performance is better than serial SGS or hybrid SGS (parallel and serial combination) as the number of activities increases (Lova & Tormos, 2001). At the same time, in a dynamic environment, the adjustment ability of parallel SGS is stronger than serial SGS (Wang et al, 2017). Therefore, this paper employed parallel SGS to accomplish the dynamic scheduling. In Villafáñez et al (2019), at each decision point, the critical path method (CPM) is used to form a temporary schedule for unscheduled activities and their priorities are recalculate (as necessary) (see Fig 2). On the basis of parallel SGS, there will be another dynamic factor of the new project arrival/insertion for SRCMPSP-NPA. Thus, before scheduling, it is necessary to judge whether there is a new project arrival/insertion. However, the time of the new project arrival/insertion is stochastic, how to simulate this random arrival time should be determined. Then the arrival/insertion condition established by this study is that the generated random number is smaller than the threshold ε and the capacity of the project does not exceed its maximum capacity. The scheduling process is shown in Fig.2.

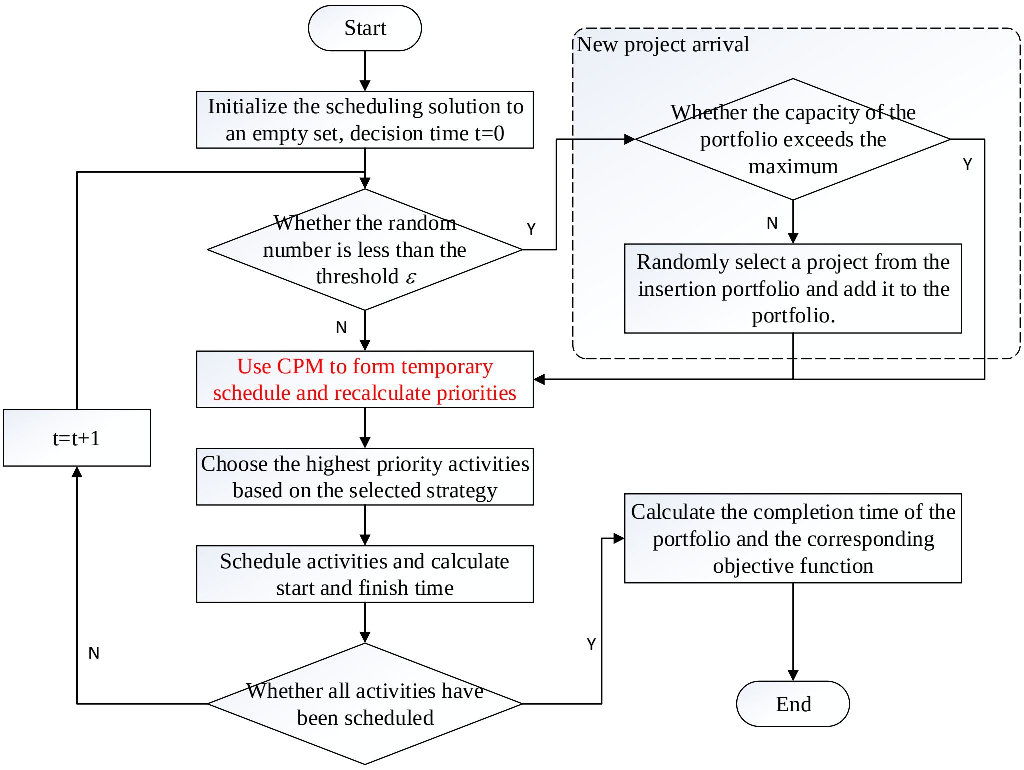

Fig.2 The flow chart of scheduling

4.2 Priority Rules

Similar to Wang et al (2017) and Browning & Yassine (2010), this study selects the same 20 PRs for SRCMPSP-NPA. The corresponding calculation formula and description are shown in Table 2.

Table 2 PRs apply to SRCMPSP-NPA

Priority rule	Calculation formula	Description
1. MINSLK Minimum slack	$\min(LS_{pa} - \max(ES_{pa}, t))$	Select the activities with the minimum slack time, where LS_{pa} and ES_{pa} represent the latest start time and the earliest start time of activity a in project p and t represents the decision time.
2. MAXSLK Maximum slack	$\max(LS_{pa} - \max(ES_{pa}, t))$	Select the activities with the maximum slack time
3. SASP Shortest activity from shortest project	$\min(CP_p + d_{pa})$	Select the activities with the minimum sum of its duration and the associated project critical path
4. LALP Longest activity from longest project	$\max(CP_p + d_{pa})$	The maximum value described in SASP
5. MINTWK Minimum total work content	$\min(\sum_{k\in K_p}\sum_{a\in AS_p} d_{pa}r_{pak} + d_{pa}\sum_{k\in K_p} r_{pak})$	Select the activities with the minimum total work about the resources and duration occupation, where AS_p refers to the activity set

		that has been scheduled in project *p*
6. MAXTWK Minimum total work content	$\max(\sum_{k\in K_p}\sum_{a\in AS_p} d_{pa}r_{pak} + d_{pa}\sum_{k\in K_p} r_{pak})$	The maximum value described in MINTWK
7. TWK-LST MAXTWK & earliest late start time	$\max(\sum_{k\in K_p}\sum_{a\in AS_p} d_{pa}r_{pak} + d_{pa}\sum_{k\in K_p} r_{pak})$ & $\min(LS_{pa})$	Select the activities with the minimum latest start time on the basis of MAXTWK
8. TWK-EST MAXTWK & earliest early start time	$\max(\sum_{k\in K_p}\sum_{a\in AS_p} d_{pa}r_{pak} + d_{pa}\sum_{k\in K_p} r_{pak})$ & $\min(ES_{pa})$	Select the activities with the minimum earliest start time on the basis of MAXTWK
9. FCFS First come first serve	$\min(ES_{pa})$	Select the activities with the minimum earliest start time
10. LCFS Last come first serve	$\max(ES_{pa})$	Select the activities with the maximum earliest start time
11. SOF Shortest operation first	$\min(d_{pa})$	Select the activities with the minimum duration
12. MOF Maximum operation first	$\max(d_{pa})$	Select the activities with the maximum duration
13. RAN Random		Random selection of activities
14. EDDF Earliest due date first	$\max(LS_{pa})$	Select the activities with the minimum latest start time
15. MINLFT Minimum late finish time	$\max(LF_{pa})$	Select the activities with the minimum latest finish time
16. MAXSP Maximum schedule pressure	$\max(\frac{t-LF_{pa}}{d_{pa}W_{pa}})$	Select the activity with the minimum "pressure", where W_{pa} is the percentage of the activity remaining to be done at time *t*
17. MINWCS Minimum worst case slack	$\min(LS_{pa}\text{-}\max(E_{(a,b)}))\quad (a,b)\in AP_t$	Select the worst case minimum slack activities, where $E_{(a,b)}$ represents the earliest start time of activity *b* if activity *a* begins at time *t*, and AP_t refers to the qualifying activity at time t
18. WACRU criticality & resource utilization	$\max(w\sum_{q\in N_a}(1+SLK_{aq})^{-\alpha}+(1-w)\sum_{k\in K_p}\frac{r_{pak}}{R_k})$	Select the most critical and least resource-intensive activities, where N_a is the immediate successor activity set of activity *a*, SLK_{aq} is the slack time of activity *a* and the *q*th immediate successor activity, *w* and α are weights set to 0.5.
19. MS Maximum total successors	$\max(TS_{pa})$	Select the activity with the most total successor number (TS_{pa}) of activities
20. MCS	$\max(CS_{pa})$	Select the activity with the most critical

Maximum critical successors	successor number (CS_{pa}) of activities

4.3 Heuristic Hybrid Methods

There are certain limitations with a single rule scheduling throughout the scheduling process, and often different priorities in different states can play better effects than most the single PR or even dominate the single PR in different environments or states (see Sect.2). Therefore, this paper proposes a heuristic hybrid method, which divides the scheduling of the entire portfolio into different phases, corresponding to different states, and can perform different rule scheduling in different states. When the portfolio is constantly going on, the rules required to make the objective function optimal or sub-optimal are different. For example, in the later stages of the entire portfolio, when one or two projects are still in progress, the resource-based rule will be less effective, because optimal scheduling in RCPSP instances is never discovered by resource-based rules (Rostami, Creemers & Leus, 2018). The completion progress of each project is determined by the critical activities on its critical path. Thus, the parameters for dividing the portfolio state are as shown in Eq. (10).

$$s = \sum_{p \in P} \sum_{a \in PC_p} d_{pa} / \sum_{p' \in P} \sum_{a' \in TC_p} d_{p'a'} \tag{10}$$

Where PC_p represents the set of critical activities that have been planned in project p, TC_p represents the set of total critical activities in project p, and s represents the planned percentage of key activities in the entire portfolio, of which corresponding state is shown in Table 3.

Table 3 State table

s	[0-0.2]	[0.2-0.4]	[0.4-0.6]	[0.6-0.8]	[0.8-1]
state	1	2	3	4	5

The heuristic hybrid method proposed in this paper can select the rules according to diverse states related to the structure of data set and the objective functions, and the detailed rule selection is introduced in Sect.5.2.

5 Experimental Results and Analysis

In order to study the performance of PRs under the SRCMPSP-NPA and verify the effectiveness of the heuristic hybrid method proposed in this paper, a series of experiments are carried out on the new data set because there is no benchmark that can be referenced based on this condition. The construction of the data set and the design of the experiment (including related parameters and methods, etc.) are shown in Sect.5.1. Sect.5.2 analyzes the performance of 20 PRs and Sect.5.3 illustrates the verification of the heuristic hybrid method.

5.1 Data Set Construction and Experiment Design

The data sets used in this paper are combined with the project elements in the benchmark

PSPLIB, which can be obtained at http://www.om-db.wi.tum.de/psplib/library.html. In the real condition, there are flexibility and diversity for the original or inserted projects, so their attributes are different, such as the number of activities, priority relationships, resource requirements, and so on. Thus, based on the number of activities, the PSPLIB is divided into 4 scales of J30 (30 activities), J60 (60 activities), J90 (90 activities) and J120 (120 activities), and each instance of the activities has different priority relationship and resource requirement. Therefore, the data set consists of a group of portfolios, each of which contains an activity of J30, J60, J90 and J120 individually. According to the order of the compressed package downloaded from the PSPLIB website, the first 200 instances of each scale projects form the 200 different basic portfolios respectively required for the experiments in this study. In addition, in accordance with this rule, subsequent 10 projects are selected from each scale as the insertion portfolio. The structure of this data set is shown in Table 4, where N_{jnum} represents the number in all projects which has *num* activities in the PSPLIB. In the insertion portfolio, all projects will be renumbered from 1 to 40 according to their activity number. For example, projects with 30 activities from 201 to 210 will be renumbered 1 to 10, and projects with 60 activities will be numbered 11 to 20, and so on. Since the SRCMPSP-NPA takes into account the dynamic factor of new project arrival/insertion, 200 instances are divided into 4 groups according to the order of compressed package, and each group will be scheduled under 5 dynamic conditions as shown in Table 5. The maximum capacity of each portfolio is set to 6, in other words, during the entire scheduling process, up to 2 new projects arrived/inserted are allowed. The threshold ε shown in Fig.2 is 0.1, and all the generated conditions have 2 new projects arriving. So in Table 5, $t_{insert1}$ and $t_{insert2}$ represent the time of the first and second new project arrival/insertion, respectively, which is controlled by the random number and the threshold ε, and p_{code} represents the inserted project index, which satisfies the uniform distribution.

Table 4 The data set

Group number	Portfolio number	No. of Component element			
		N_{j30}	N_{j60}	N_{j90}	N_{j120}
1	$Portfolio_1$	1	1	1	1
	…		…		
	$Portfolio_{50}$	50	50	50	50
2	$Portfolio_{51}$	51	51	51	51
	…		…		
	$Portfolio_{100}$	100	100	100	100
3	$Portfolio_{101}$	101	101	101	101
	…		…		
	$Portfolio_{150}$	100	100	100	100
4	$Portfolio_{151}$	151	151	151	151
	…		…		
	$Portfolio_{200}$	200	200	200	200
Insertion portfolio		201 to 210	201 to 210	201 to 210	201 to 210

Table 5 New project arrival/insert table

Group	Condition	$t_{insert1}$	p_{code}	$t_{insert2}$	p_{code}
1	1	10	19	37	29

	2	1	16	10	22
	3	0	8	19	30
	4	10	31	14	33
	5	11	7	29	17
	1	11	22	44	39
	2	10	21	23	25
2	3	58	14	85	23
	4	14	39	33	33
	5	9	20	18	40
	1	0	37	16	18
	2	5	27	6	34
3	3	2	9	5	20
	4	16	26	27	40
	5	12	34	20	37
	1	17	26	34	6
	2	4	35	7	39
4	3	2	10	4	16
	4	14	40	34	13
	5	1	8	18	39

After building the basic portfolio and insertion portfolio, the second dynamic factor, the stochastic duration of activity, is assumed to satisfy a particular distribution. 5 common distributions (Chen et al, 2018) are adopted in this paper and shown in Table 6. These 5 distributions cover 2 low variance distributions (U1 & B1), 2 medium variance distributions (U2 & B2) and 1 high variance distribution (E), which can fully test the robustness of different PRs and the heuristic hybrid method under different conditions. In Table 6, d'_{pa} represents the duration with a deterministic environment of activity a in project p in PSPLIB.

Table 6 5 distributions of activity duration

Distribution type	Code	Range	Variance
Uniform distribution	U1	$U(d'_{pa}-\sqrt{d'_{pa}}, d'_{pa}+\sqrt{d'_{pa}})$	$d'_{pa}/3$
	U2	$U(0, 2d'_{pa})$	$(d'_{pa})^2/3$
Beta distribution	B1	$B(d'_{pa}/2, 2d'_{pa}, d'_{pa}/2-1/3, d'_{pa}-2/3)$	$d'_{pa}/3$
	B2	$B(d'_{pa}/2, 2d'_{pa}, 1/6, 1/3)$	$(d'_{pa})^2/3$
Exponential distribution	E	$E(d'_{pa})$	$(d'_{pa})^2$

The experiment will be carried out based on this dataset and an experimental parameter that is not mentioned above and the way of the experiment needs to be explained. The parameter R_k (maximum resource unit supply) in Table 1 greatly affects the quality of the scheduling solution. For example, if it is too big, there is basically no conflict in the scheduling process, and the finish time of each project will be equal to the length of its critical path, so that the scheduling experiment loses its value. In PSPLIB, the maximum resource requirement category for each activity is 4, and the maximum demand for each resource is 10. In the experiment, the R_k of each resource is set to 20 because it means that at least 2 activities can be operated at each time if all activities have a demand for such resource is 10. In addition, the objective function of this study is as shown in Eq.(6) to Eq.(9), so the objectives in two environments are designed, which are the deterministic (calculate Q_1 & Q_2) and stochastic duration (calculate R_1 & R_2), respectively. Therefore, under each different experimental input (a portfolio with a condition), the deterministic environment is executed once. The stochastic environment is performed 10 times to calculate the SAD_p in Eq.(8) and Eq.(9).

5.2 20 PRs Scheduling Performance Exploration

This section is mainly to explore the performance of 20 PRs under the new data set designed in Sect.5.1. Firstly, the performance evaluation methods of PRs will be introduced. On this basis, the performance is analyzed from three perspectives: project, portfolio and global. All program code is written in Java on the MyEclipse 2017 compiler and all experiments are performed on an Intel Core i5-4200 quad-core processor computer with 2.50 gigahertz clock speed and 8 gigabyte RAM.

5.2.1 Evaluation method

The evaluation method of this research mainly refers to Wang et al (2017). Under each experimental input, using the different PRs schedules will get the corresponding 4 objective function values, so that under each objective function value, 20 PRs will produce a superior ranking. The evaluation and analysis of the pros and cons of each PR depends on their average ranking under 1000 experimental inputs (200 portfolios×5 conditions). Simultaneously, in order to more fully consider the corresponding requirements that the quality or robustness of the solution is more important in some cases, the number of Pareto fronts for each PR will be counted, providing some advice for these situations.

5.2.2 Performance analysis

The average sequence of the 20 PRs under the five distributions is shown in Table 7. From Table 7, we can see the average ranking of objective function values of PRs under all distributions. Then, in the project perspective and portfolio perspective, the Pareto frontier number and the corresponding two objective function averages are used to evaluate, and the evaluation index based on global perspective is the average of the four objective functions.

Table 7 The average ranking of the 20 PRs

Rule			U1		U2		B1		B2		E	
	Q_1	Q_2	R_1	R_2	R_1	R_2	R_1	R_2	R_1	R_2	R_1	R_2
MINSLK	3.868	5.110	8.926	8.234	10.858	8.932	10.169	7.930	11.067	10.507	12.917	10.658
MAXSLK	16.678	19.282	10.739	10.789	9.265	10.053	11.220	10.805	9.350	9.597	7.725	9.348

SASP	**3.335**	14.123	11.639	10.634	15.545	12.348	12.739	11.562	15.877	10.637	17.145	11.447
LALP	15.256	13.073	9.603	9.778	12.501	9.717	9.356	9.894	12.289	9.532	13.374	9.159
MINTWK	8.589	14.241	**4.824**	8.336	**3.165**	8.888	**3.369**	9.546	**3.503**	9.593	3.776	9.006
MAXTWK	10.045	13.822	16.825	15.362	17.110	13.865	16.779	14.536	16.728	12.272	16.593	11.875
TWKLST	9.901	13.743	16.805	15.246	17.087	14.145	16.751	14.404	16.927	12.483	16.728	11.882
TWKEST	10.131	13.888	16.883	15.220	17.211	14.183	16.752	14.603	16.909	12.219	16.804	11.407
FCFS	3.878	10.005	7.503	7.655	8.715	10.605	8.282	9.178	8.825	11.733	10.313	12.256
SOF	12.524	14.346	12.675	12.185	12.438	10.631	13.490	11.871	12.302	8.377	10.375	8.592
MOF	15.288	16.418	11.480	11.308	11.150	9.600	11.138	10.230	10.194	10.592	10.549	10.727
RAN	14.496	13.185	11.310	10.078	9.895	9.235	11.874	10.420	9.851	9.106	8.256	9.079
EDDF	3.868	5.110	8.830	8.117	10.883	8.976	10.220	7.950	11.075	10.527	12.764	10.427
LCFS	3.878	10.005	7.496	7.671	8.779	10.009	8.425	9.277	8.790	11.743	10.404	12.314
MINLFT	5.933	5.518	13.513	12.700	13.963	10.835	14.497	11.749	13.997	9.601	12.805	10.095
MAXSP	18.074	2.568	7.334	8.423	4.860	8.951	5.165	7.206	5.184	10.239	4.549	10.959
MINWCS	4.843	10.891	7.826	**7.546**	8.938	10.322	8.793	9.353	9.075	11.844	10.428	12.134
WACRU	13.714	**1.876**	10.273	11.081	7.924	8.728	9.803	9.743	7.511	**7.755**	5.899	**7.817**
MS	17.862	1.938	6.370	8.084	3.303	**8.053**	3.707	**6.573**	3.774	9.752	**3.217**	9.881
MCS	15.065	6.003	7.526	9.031	5.434	8.647	6.175	8.444	5.773	9.249	4.690	8.946

Project perspective

From the average of Q_1 and R_1 in Table 7, the rankings at the project perspective can be obtained as shown in Table 8. As can be seen from Table 7 and Table 8, the superiority of SASP in terms of the solution quality ranking is much stronger than that of other PRs, which is consistent with the conclusions obtained by Kurtulus & Davis (1982) and Tsubakitani & Deckro (1990). However, its robustness is poor, especially under high variance distribution, which lowers its comprehensive ranking in the project perspective. MS has some advantages in terms of robustness, but its poor-quality leads to a bad ranking. MINTWK, FCFS and LCFS have a better overall ranking regardless of the distribution, and the robustness of MINTWK in the project perspective (R_1) is the best in almost all distributions, so these three rules are the best when choosing from the project perspective.

Table 8 Project perspective ranking

U1	U2	B1	B2	E
LCFS	MINTWK	MINTWK	MINTWK	MINTWK
FCFS	FCFS	FCFS	LCFS	FCFS
MINWCS	LCFS	LCFS	FCFS	LCFS
EDDF	MINWCS	MINWCS	MINWCS	MINWCS
MINSLK	MINSLK	MINSLK	MINSLK	EDDF
MINTWK	EDDF	EDDF	EDDF	MINSLK
SASP	SASP	SASP	SASP	MINLFT
MINLFT	MINLFT	MINLFT	MINLFT	WACRU
MCS	MCS	MCS	MCS	MCS
WACRU	MS	MS	WACRU	SASP
MS	WACRU	MAXSP	MS	MS
LALP	MAXSP	WACRU	MAXSP	MAXSP

SOF	RAN	LALP	RAN	RAN
MAXSP	SOF	SOF	SOF	SOF
RAN	MAXSLK	RAN	MOF	MAXSLK
TWKLST	MOF	MOF	MAXSLK	MOF
MOF	TWKLST	TWKLST	MAXTWK	TWKLST
MAXTWK	MAXTWK	MAXTWK	TWKLST	MAXTWK
TWKEST	TWKEST	TWKEST	TWKEST	TWKEST
MAXSLK	LALP	MAXSLK	LALP	LALP

On the other hand, the Q_1 value and the R_1 value obtained by randomly selecting an experimental input in the low variance distribution (U1) and the high variance distribution (E) are shown in Fig.3 and Fig.4. In order to compare the distribution of values more clearly, the percentages are used, and the following figures are the same. The statistical table of the Pareto frontier number for each PR with 1000 inputs is shown in Table 9. Table 9 contains the Pareto frontier number for each PR of the project and portfolio, where pro_{num} represents the project perspective while por_{num} represents the portfolio perspective.

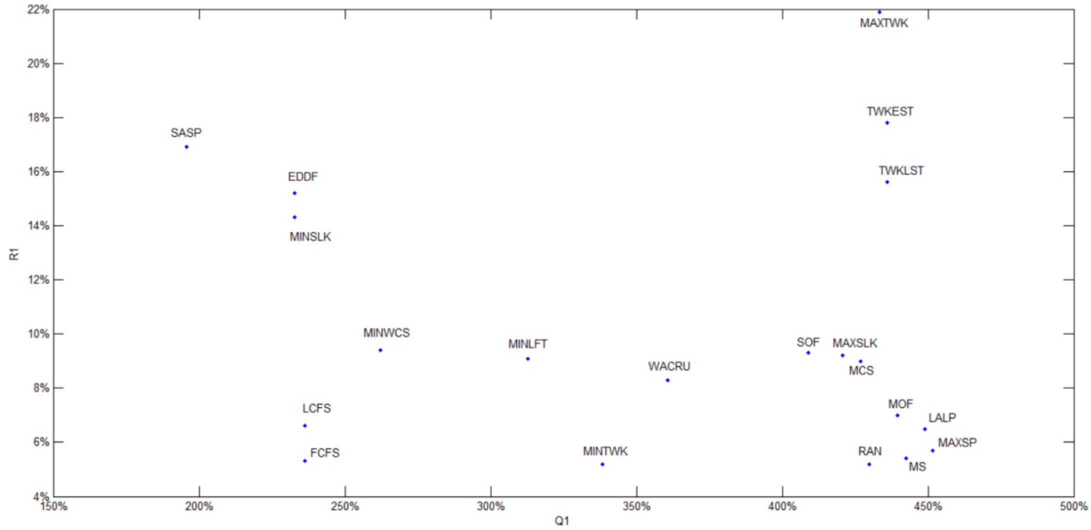

Fig.3 The Q_1 and R_1 of different PRs under the low variance distribution

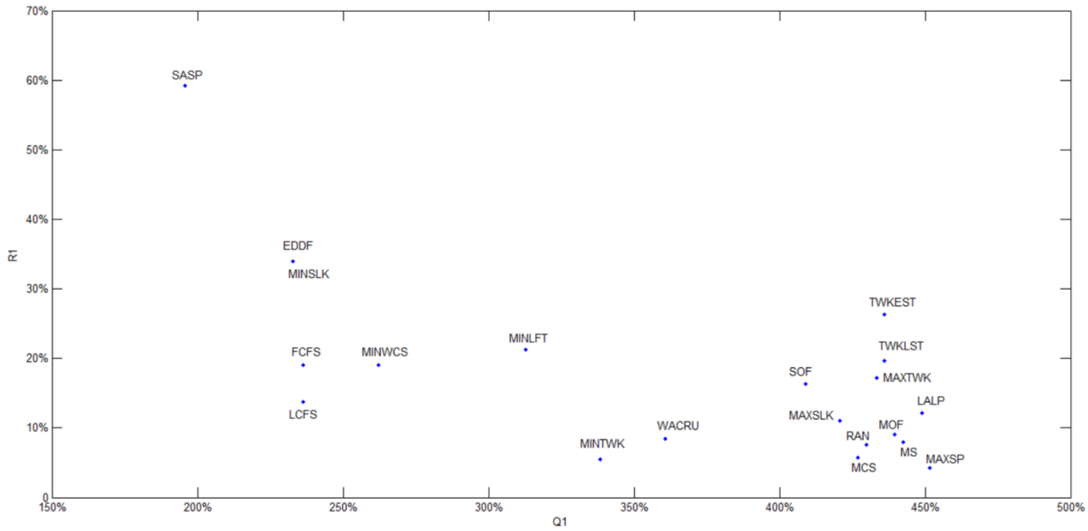

Fig.4 The Q_1 and R_1 of different PRs under the high variance distribution

Table 9 The statistical table of the Pareto frontier number

Rule	U1		U2		B1		B2		E	
	pro_{num}	por_{num}	pro_{num}	por_{num}	pro_{num}	por_{num}	pro_{num}	por_{num}	pro_{num}	por_{num}
MINSLK	404	205	501	34	455	71	519	39	460	10
MAXSLK	32	25	31	23	14	3	29	12	68	33
SASP	**520**	40	497	2	545	12	503	1	483	0
LALP	75	76	11	10	51	22	13	14	4	2
MINTWK	401	224	**808**	277	**751**	268	**761**	265	**814**	214
MAXTWK	35	4	38	5	34	4	37	6	37	6
TWKLST	38	7	33	3	44	7	33	2	37	3
TWKEST	43	6	32	2	35	4	34	5	35	4
FCFS	515	184	640	67	588	89	648	56	659	23
SOF	35	23	17	6	8	6	22	9	56	20
MOF	38	33	19	12	13	15	28	16	26	13
RAN	35	41	26	12	11	12	40	26	60	27
EDDF	396	199	493	29	440	68	503	30	484	6
LCFS	467	183	619	58	566	78	641	51	640	13
MINLFT	174	72	236	26	172	30	244	20	339	23
MAXSP	90	495	229	500	249	537	200	509	195	478
MINWCS	377	161	510	38	457	68	503	39	512	13
WACRU	59	665	109	652	66	638	166	690	251	692
MS	96	**716**	431	**813**	425	**834**	338	**779**	369	**763**
MCS	133	262	247	179	210	168	260	199	313	225

As can be seen from Fig.3 (Pareto frontier rank is SASP, FCFS, MINTWK in order) and Fig.4 (Pareto frontier rank is SASP, LCFS, MINTWK in order), in more than half of the cases, the solution quality (Q_1) of SASP is excellent, but its robustness is poor, and as the uncertainty of distribution increases, its robustness deteriorates more severely, resulting in a decline in its ranking as shown in Table 8. At the same time, MINTWK has superior robustness (R_1) and is less affected by the distribution, so its Pareto frontier number is dominant compared to other PRs as shown in Table 9. The FCFS and LCFS rules have good comprehensive performance, that is, the Q_1 and the R_1 are outstanding. Thus, as seen in Table 9, their Pareto fronts are also leading. Therefore, in SRCMPSP-NPA, for the project manager, if the stability is not considered, SASP is definitely the best choice. If the robustness and quality are to be considered comprehensively, then MINTWK, FCFS and LCFS should be selected.

Portfolio perspective

In portfolio perspective, the ranking of the PRs based on the average of Q_2 and R_2 for the 5 distributions are shown in Table 10. The Q_2 and R_2 of one experimental input under U1 and E are shown in Fig.5 and Fig.6.

Table 10 Portfolio perspective ranking

U1	U2	B1	B2	E
MS	MS	MS	WACRU	WACRU
MAXSP	WACRU	MAXSP	MS	MS
WACRU	MAXSP	WACRU	MAXSP	MAXSP

EDDF	MINSLK	MINSLK	MINLFT	MCS
MINSLK	EDDF	EDDF	MCS	EDDF
MCS	MCS	MCS	MINSLK	MINLFT
FCFS	MINLFT	MINLFT	EDDF	MINSLK
LCFS	LCFS	FCFS	FCFS	LALP
MINLFT	FCFS	LCFS	LCFS	FCFS
MINWCS	MINWCS	MINWCS	RAN	RAN
MINTWK	RAN	LALP	LALP	LCFS
LALP	LALP	RAN	SOF	SOF
RAN	MINTWK	MINTWK	MINWCS	MINWCS
SASP	SOF	SASP	MINTWK	MINTWK
SOF	MOF	SOF	SASP	TWKEST
MOF	SASP	MOF	MAXTWK	SASP
TWKLST	MAXTWK	TWKLST	TWKEST	TWKLST
TWKEST	TWKLST	MAXTWK	TWKLST	MAXTWK
MAXTWK	TWKEST	TWKEST	MOF	MOF
MAXSLK	MAXSLK	MAXSLK	MAXSLK	MAXSLK

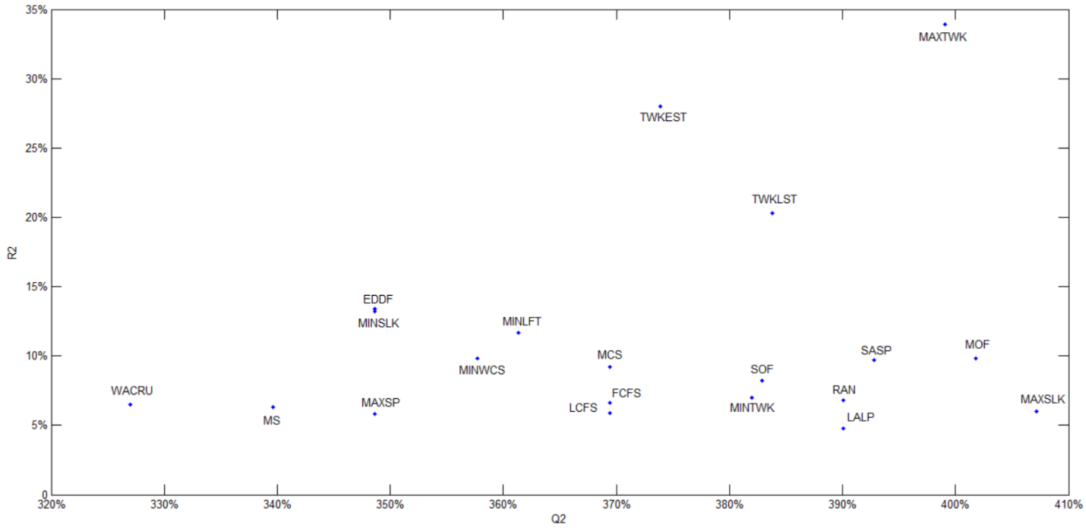

Fig.5 The Q_2 and R_2 of different PRs under the low variance distribution

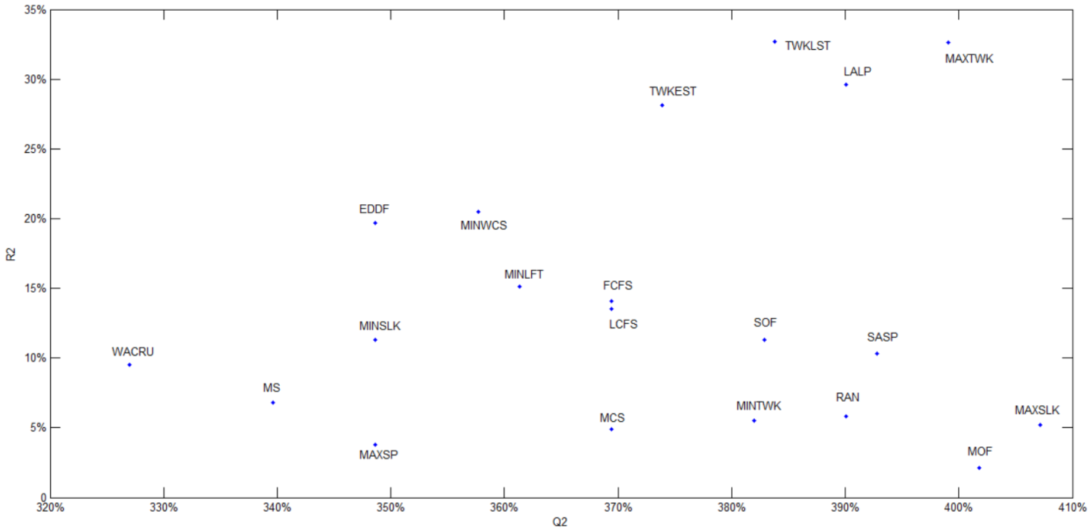

Fig.6 The Q_2 and R_2 of different PRs under the high variance distribution

In the portfolio perspective, MS, WACRU and MAXSP are absolutely dominant compared to other PRs. As can be seen from Fig. 5, Fig. 6 and Table 9, in most cases, the pareto front of this perspective comes from these three PRs, and the pareto frontier number of the remaining PRs is almost tens or even several times. It is worth mentioning that as the distribution variance increases, it can be seen from Table 7 and Table 10 that the robustness of WACRU is better than that of MS, and thus its ranking gradually increases. Thus, for the portfolio manager, MS (under low variance) and WACRU (under medium or high variance) are the most recommended rules, and MAXSP is a recommended alternative to these two PRs in SRCMPSP-NPA.

Global perspective

The rankings obtained from a global perspective (integrated project and portfolio perspectives) are calculated from the average of the Q_1, Q_2, R_1, and R_2 as shown in Table 11. Although MINSLK and EDDF are not the best in both project and portfolio, their comprehensive performance is optimal under low or medium variance and the difference between the two PRs is small as shown in Table 7. This conclusion is consistent with Wang et al (2017), that the performance of PRs in SRCMPSP (EDDF is optimal and MINSLK is second. In addition, due to the superior robustness of WACRU, its ranking continues to rise with the increasing of distribution variance, and its comprehensive ranking has surpassed other PRs under high variance distribution. In summary, MINSLK and EDDF are the primary recommendations in the SRCMPSP-NPA for considering global performance, and WACRU is suggested under high variance distribution scheduling.

Table 11 Global perspective ranking

U1	U2	B1	B2	E
EDDF	MINSLK	MINSLK	MINSLK	WACRU
MINSLK	EDDF	EDDF	EDDF	EDDF
FCFS	MS	MS	WACRU	MINSLK
LCFS	WACRU	FCFS	MS	MS
MINWCS	LCFS	LCFS	LCFS	MINLFT
MS	FCFS	MAXSP	FCFS	MCS
MINTWK	MAXSP	MINWCS	MINLFT	MINTWK
MAXSP	MINTWK	WACRU	MINTWK	MAXSP
WACRU	MINWCS	MCS	MAXSP	FCFS
MCS	MCS	MINTWK	MCS	LCFS
MINLFT	MINLFT	MINLFT	MINWCS	MINWCS
SASP	SASP	SASP	SASP	RAN
LALP	RAN	LALP	RAN	SOF
RAN	SOF	RAN	SOF	SASP
SOF	LALP	SOF	LALP	LALP
MOF	MOF	MOF	MOF	TWKEST
TWKLST	MAXTWK	TWKLST	MAXTWK	TWKLST
MAXTWK	TWKLST	MAXTWK	TWKLST	MAXTWK
TWKEST	MAXSLK	TWKEST	TWKEST	MOF
MAXSLK	TWKEST	MAXSLK	MAXSLK	MAXSLK

5.3 Heuristic hybrid method verification

Since a single PR scheduling still has certain defects, even the best comprehensive performance of EDDF in Sect.5.2 is not as good as SASP (Q_1) or MS (Q_2) in quality, and is not as robust as MS and WACRU under most distributions. Therefore, this section carries out the verification of the heuristic hybrid method proposed in Sect.4.3. Sect.5.3.1 will introduce the selection method and reason of PRs and the analysis of the experimental results is described in Sect.5.3.2.

5.3.1 PRs selection

For project perspective, its calculation is related to the critical path length of each project. When some projects with small critical path length are scheduled to be completed, the competition of resources will be small or even resources will be released, which is more conducive to later scheduling. If the project with a shorter critical path length in the portfolio is later scheduled, the deterioration of Q_1 is more serious. In the early stage of scheduling, the project scheduling with smaller critical path should be selected (especially if the number of activities in each project is different). Therefore, the attribute of the earliest start time (ES_{pa}) should be paid more attention (At each decision point, the ES_{pa} of each activity in an eligible set is updated according to the temporary schedule generated by the critical path method), and thus LCFS, FCFS and MINWCS are selected. For portfolio perspective, the impact is only related to the duration of the portfolio or the maximum duration of the project. Thus, theoretically, if the later activities should be arranged as soon as possible in a schedulable set, and the Q_2 value will be optimized, that is, rules related to the last start time attribute (LS_{pa}) can be selected. MINSLK and EDDF can enable this . Therefore, in order to improve the comprehensive performance, according to this condition, the heuristic hybrid method of this study selects the first two stages to adopt one of LCFS, FCFS and MINWCS for scheduling, while the latter three stages use one of MINSLK and EDDF to form 6 heuristic hybrid strategies (LCFS-SLK, LCFS-EDDF, FCFS-SLK, FCFS-EDDF, WCS-SLK, WCS-EDDF).

5.3.2 Performance analysis

The Q (the average of the rankings under Q_1 and Q_2) ranking and the R (the average of the rankings under R_1 and R_2) ranking obtained by the 6 hybrid strategies and 20 PRs under different variance distribution are shown in Table 12, and the global ranking table is shown in Table 13, where *avg* represents the average of the rankings under Q_1, Q_2, R_1 and R_2.

Table 12 Q ranking and R ranking under different variance distribution

Rule	Q	R				
		U1	U2	B1	B2	E
MINSLK	7.416	11.713	12.967	12.060	13.927	14.993
MAXSLK	23.979	14.588	12.570	14.647	12.137	10.487

SASP	13.049	14.966	18.440	16.238	17.343	18.547
LALP	19.910	13.113	14.610	12.755	14.120	14.361
MINTWK	17.150	8.893	7.602	8.412	8.097	7.701
MAXTWK	17.527	21.308	20.315	20.685	18.902	18.356
TWKLST	17.388	21.172	20.484	20.571	19.146	18.436
TWKEST	17.607	21.226	20.578	20.722	18.951	18.181
FCFS	11.615	10.171	12.468	11.480	13.111	14.113
SOF	19.378	16.722	15.220	16.892	13.375	11.839
MOF	21.835	15.382	13.552	14.198	13.354	13.356
RAN	19.787	14.467	12.423	14.783	12.113	10.613
EDDF	7.416	11.565	13.016	12.088	13.918	14.718
LCFS	11.615	10.213	12.115	11.638	13.092	14.232
MINLFT	8.983	17.656	16.394	17.525	15.368	14.584
MAXSP	13.364	10.701	8.840	8.204	9.679	9.478
MINWCS	12.791	10.350	12.432	11.972	13.392	14.092
WACRU	10.897	14.424	10.704	12.921	9.593	8.261
MS	12.927	9.849	7.218	6.742	8.459	7.959
MCS	14.71	11.259	9.009	9.628	9.401	8.277
WCS-EDDF	6.802	11.280	12.523	11.887	13.354	14.265
WCS-SLK	6.802	11.163	12.710	11.932	13.598	14.177
FCFS-EDDF	5.753	11.182	12.583	11.904	13.273	14.326
FCFS-SLK	5.753	11.107	12.611	11.793	13.471	14.559
LCFS-EDDF	5.759	11.215	12.910	11.748	13.130	14.352
LCFS-SLK	5.759	11.267	12.723	11.746	13.350	14.367

Table 13 Global ranking under different variance distribution

U1		U2		B1		B2		E	
Rule	*avg*	Rule	*avg*	Rule	*avg*	Rule	*avg*	Rule	*avg*
FCFS-SLK	8.430	FCFS-EDDF	9.168	LCFS-SLK	8.753	LCFS-EDDF	9.445	WACRU	9.579
FCFS-EDDF	8.468	FCFS-SLK	9.182	LCFS-EDDF	8.754	FCFS-EDDF	9.513	FCFS-EDDF	10.040
LCFS-EDDF	8.487	LCFS-SLK	9.241	FCFS-SLK	8.773	LCFS-SLK	9.556	LCFS-EDDF	10.056
LCFS-SLK	8.513	LCFS-EDDF	9.335	FCFS-EDDF	8.829	FCFS-SLK	9.612	LCFS-SLK	10.063
WCS-SLK	8.983	WCS-EDDF	9.663	WCS-EDDF	9.345	WCS-EDDF	10.078	FCFS-SLK	10.156
WCS-EDDF	9.041	WCS-SLK	9.756	WCS-SLK	9.367	WCS-SLK	10.200	MS	10.443
EDDF	9.491	MS	10.073	MINSLK	9.738	WACRU	10.245	WCS-SLK	10.490
MINSLK	9.565	MINSLK	10.192	EDDF	9.752	EDDF	10.667	WCS-EDDF	10.534
FCFS	10.893	EDDF	10.216	MS	9.835	MINSLK	10.672	EDDF	11.067
LCFS	10.914	WACRU	10.801	MAXSP	10.784	MS	10.693	MINSLK	11.205
MS	11.388	MAXSP	11.102	FCFS	11.548	MAXSP	11.522	MAXSP	11.421
MINWCS	11.571	MCS	11.860	LCFS	11.627	MCS	12.056	MCS	11.494
MAXSP	12.033	LCFS	11.865	WACRU	11.909	MINLFT	12.176	MINLFT	11.784
WACRU	12.661	FCFS	12.042	MCS	12.169	LCFS	12.354	MINTWK	12.426
MCS	12.985	MINTWK	12.376	MINWCS	12.382	FCFS	12.363	FCFS	12.864
MINTWK	13.022	MINWCS	12.612	MINTWK	12.781	MINTWK	12.624	LCFS	12.924

MINLFT	13.320	MINLFT	12.689	MINLFT	13.254	MINWCS	13.092	MINWCS	13.442
SASP	14.008	SASP	15.745	SASP	14.644	SASP	15.196	RAN	15.200
LALP	16.512	RAN	16.105	LALP	16.333	RAN	15.950	SOF	15.609
RAN	17.127	LALP	17.260	RAN	17.285	SOF	16.377	SASP	15.798

As can be seen from Table 12, the more unstable the distribution, the smaller the difference in robustness of most single or hybrid PRs. Simultaneously, comparing Table 7 to Table 11, after adding new PRs, the global ranking of some rules may change. But the 6 hybrid PRs can improve the *Q* ranking compared to the original PRs and hardly affect or deteriorate the *R* ranking shown in Table 12. Therefore, the global performance of the 6 hybrid PRs is better than the original PRs regardless of the distribution variance and their global ranking is superior to the single PR under a low or medium variance distribution shown in Table 13. In the first 4 distributions, the average percentage of the global rankings of the 6 hybrid PRs leading that of the best single PR is 8.82%,6.77%,7.88% and 4.99%, respectively. Under the exponential distribution, because WACRU has better robustness than 6 hybrid PRs, the global ranking of 6 hybrid rules does not exceed WACRU, and its average backward percentage is 6.29%. In summary, the experimental results of this study can verify that the hybrid method has better global performance and is effective and superior under most distributions.

6 Conclusions

This paper first takes into account two dynamic factors commonly found in a real problem, the stochastic duration and the new projects arrival, then develops the traditional RCMPSP into SRCMPSP-NPA, and finally establishes the corresponding mathematical model and its solution. Based on the performance evaluation, we can conclude this paper as follows.

1) By mathematically modeling two dynamic factors, SRCMPSP-NPA is a more precise industrial application problem that can comprehensively consider the solution quality and robustness;

2) 20 PRs from existing research are evaluated from three perspectives (project, portfolio and global) and it is found that they are not equally effective for difference perspectives. For the project perspective, if the solution quality is more focused, SASP is our recommendation, and if the robustness and quality are both considered, MINTWK, FCFS and LCFS are good choices. For the portfolio perspective, MS, WACRU and MAXSP are recommended. While for the global perspective, MINSLK, WACRU and EDDF rank higher than other PRs in different distributions. MINSLK and EDDF are suitable for the low or medium variance distributions while WACRU is suitable for the high variance distribution. They are the best PR performed in our experiments and are our strongest recommendation.

3) The proposed heuristic hybrid method can solve SRCMPSP-NPA more effectively by selecting different PRs to schedule the portfolio in different states.Six hybrid scheduling PRs, LCFS-SLK, LCFS-EDDF, FCFS-SLK, FCFS-EDDF, WCS-SLK, WCS-EDDF have better global performance than the original rules before combination and are more effective than any other single PR under most distributions.

In future research, we will make efforts mainly from the following two aspects. The first is to make more precise modeling according to different actual situations, such as constraint (considering some special faults and resource uncertainties) and objective function (considering production cost and overdue penalty function), so that multi-project scheduling can be applied more accurately and flexibly. Secondly, through the analysis of attribute characteristics, this paper verifies that it is effective to use different PRs for scheduling in different stages. However, there are still some problems, such as whether there is a better combination (such as the combination of three rules in different stages), whether the same stage should adopt a single priority, and so on. Some learning-based strategies (reinforcement learning) will be adopted to study and analyze these problems to enable intelligent scheduling and decision making.

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