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A Multi-PR Heuristic for Distributed Multi-Project Scheduling With Uncertain Duration

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ABSTRACT Multiple projects are often managed and run in a decentralized setting. In this paper, considering the uncertainty in project implementation, we study the distributed multi-project scheduling problem with uncertain duration. A multi-PR heuristic (MPR-H) is then proposed to dynamically coordinate the global resource conflicts while minimizing the expected total tardiness cost. Three priority rules based on current known information are also proposed and incorporated in our approach. We further consider the opportunistic behaviour of self-interested agents and design a payment negotiation process which is added to the MPR-H. In this paper, we then evaluate the performance of the MPR-H on the benchmark dataset MPSPLIB. The computational results confirm that MPR-H achieves significant improvements in comparison with several state-of-the-art distributed/centralized algorithms. The proposed algorithm also provides the senior manager with an efficient method to allocate global resources for large-size and strong conflicting instances under various activity duration distributions. Besides, we show that multi-projects with relative slack global resource constraints are more affected by the change of uncertainty. By analyzing the strategic behaviour of the agents in problems with two projects, we also show that in our MPR-H with payment negotiation approach, rational agents have to behave truthfully that is the dominant-strategy equilibrium leading to high-quality results.

INDEX TERMS Heuristic algorithms, multi-project scheduling, priority rule, uncertainty.

I. INTRODUCTION

Business firms often manage multiple projects simultaneously to improve their return of investment [1]. Therefore, as a generalization of the resource-constrained project scheduling problem (RCPSP) [2], the resource-constrained multi-project scheduling problem (RCMPSP) is quite pervasive in today's project management. Classical multi-project scheduling is centralized, where information is perfectly shared among the projects and multiple projects regarded as a super project are then all scheduled by a sole decision-maker, where many approaches were proposed in this research area [3]–[5].

With the rapid development of the Internet technology and globalization, the multi-project environment is becoming more distributed, where projects might be located at various places and each project is managed by an individual decision-maker (i.e., a project manager) [6]. In such cases, the project managers independently schedule all activities within the respective projects. They then compete with each other for the resources that are shared among the projects (i.e., global resources). If the global resources are sufficient, the whole multi-project is regarded as a series of single project scheduling problems and solved independently. The global resources are however often limited and even scarce. Therefore, this becomes a distributed resource-constrained multi-project scheduling problem (DRCMPSP) [7].

In practice, several multi-project scheduling problems are run and managed in a distributed context. Instances include supply chain management [8]–[10], collaborative engineering [11], and service maintenance [12], [13]. In DRCMPSP, the projects share limited global resources and each project is scheduled by an individual project manager. Project managers pursue completing their projects as quickly as possible without often having information about other projects. Therefore, the local decisions taken by the project managers are required to be coordinated to address global resource conflicts. Nevertheless, the senior manager who is in charge of allocating the global resources to maximize social welfare, does not have detailed information about the local schedules.

We note that an effective resource allocation strategy is inseparable from the information exchange between the project managers. The allocation of global resources in

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DRCMPSP is challenged by the asymmetricity and uncertainty of the information. In practice, projects are subject to considerable uncertainty due to a variety of reasons. For instance, the project scope may change, resources may become unavailable, weather conditions may cause delays to some activities, etc. A direct result of uncertain factors is the deviation of the activity duration from the expected time, leading to the infeasibility of the pre-established schedule. Therefore, an effective coordination strategy based on information exchange between the managers is the key to address the challenges with the DRCMPSP under uncertain duration (DRCMPSP-UD).

In this paper, we propose a multi-PR (priority rule) based heuristic (MPR-H) approach which dynamically determines the global resource allocation at each decision point. Our proposed approach feedbacks the si mulation results of various PR-heuristics, and design three new PRs which are based on current or simulation information. We also test the approach on the MPSPLIB (Multi-Project Scheduling Problem LIBraray) datasets. The results show that our approach leads to significant improvements in comparison to several competitive distributed/centralized algorithms. The results also confirm that the proposed approach provides the senior manager with an efficient method to allocate the global resources even for large-size and strong conflicting instances with various distributions of the activity duration.

Furthermore, considering opportunistic project managers (e.g. who may disclose false information), we design a payment negotiation procedure combined with the MPR-H which provides a strategy that counteracts on the agents' untruthful behaviour for problems with two projects. We analyze managers' different strategy selections by experiments and give insights regarding the effectiveness of different behavioural choices and suggest rational strategies for the project managers.

The remainder of this paper is organized as follows: the related works are briefly reviewed in Section 2. In Section 3 we describe the problem in detail. In Section 4, we propose the multi-PR based heuristic approach. In Section 5, we present the computational results and their analysis. The conclusion of this paper is presented in Section 6 which also includes discussion on the limitations of this work and possible future research.

II. LITERATURE REVIEW

Given their distributed nature, multi-agent systems (MAS) is generally employed in the DRCMPSP. A MAS is a distributed system including a set of autonomous, independent, and self-interested agents, who play the roles of project and the senior managers in the DRCMPSP. To address the issue of global resource conflicts, the existing studies are focused on designing effective resource coordination mechanisms (e.g., including auction-based mechanisms and negotiation mechanisms) to realize information exchange between agents to achieve efficient resource allocation plans for DRCMPSP. Most of the existing works are however focused on deterministic DRCMPSP, only a few provide solutions for DRCMPSP with uncertain duration.

In the auction-based mechanisms, the project agents (e.g., project managers) act as the bidders for the time slots of global resources. The coordination agent (i.e., the senior manager) is the auctioneer determining the winner in each round of the auction. In the existing research works, considering the probable strategic behaviour of agents, it is essential to assume that the project agent submits their true bid price in the auction process.

Lee *et al.* [6] proposed a dynamic economy multi-agent system (MAS) model to maximize the revenue of the multi-project. Their approach is based on a market-based mechanism, where the coordinator decides the winner of the auction according to the bids submitted by the project agents. Confessore *et al.* [7] employed a MAS to model DRCMPSP with the assumption of the one-unit global resource. An iterative combinatorial auction mechanism was then designed to solve the resource conflicts for small-scale problems. Araúzo *et al.* [12] also introduced a MAS to characterize the combinatorial auction process. They proposed a dynamic programming procedure to solve the bidding problem and a sub-gradient optimization algorithm to determine the winner. In this approach, to resolve the resource conflicts, the project agents adjust the bids to the changing price of global resources set by the auctioneer.

Adhau *et al.* [14], [15] proposed a multiunit combinatorial auction-based negotiation approach based on MAS (DMAS/ABN) to solve the DMPSP with to minimize the average project delay (APD). In their approach, the resource requirements of eligible activities and the bid prices were submitted to the auctioneer. The auctioneer then employed a heuristic procedure to determine the winner in each auction round. They further implemented experiments on large instances to test their algorithm. Lim *et al.* [16] proposed an iterative bidding mechanism to coordinate the resource allocation in multiple manufacturing plants. They then employed the genetic algorithm to solve the bidding problem.

Song *et al.* [17] also used the multiunit combinatorial auction framework to handle DRCMPSP. In their method, for each auction round, the project agents participated in the auction procedure with the required resources and the value of the bids. A greedy strategy and a branch-and-bound approach were then employed by the auctioneer to determine the winner. Zhang & Chen [18] studied the multi-mode distributed multi-project scheduling problem of the wind power plant construction. A hierarchical decision-making model was then established based on the MAS, where the auction agent allocated global resources and project agents were responsible for the local project scheduling. They verified the performance of their auction mechanism by an experimental study for the wind power plant construction carried out by Datang company.

In negotiation mechanisms, agents exchange information with each other via some interaction protocols different from the fixed framework in auction-based mechanisms. It is also assumed that agents disclose true information during the negotiation process.

Lau *et al.* [19], [20] modelled the supply chain network with a MAS and developed a negotiation-based algorithm, where agents iteratively proposed and counter-proposed the start times of the operations until an acceptable agreement was achieved. Homberger [21] presented a restart evolution strategy based on MAS to coordinate the global resource conflicts. Based on [21], a (μ,λ)-coordination mechanism was also designed to allocate shared resources in [13]. In the proposed negotiation process, λ candidate contracts, as offspring, were generated by each project agent, and μ contracts were selected based on the local objectives. A mediator agent then determined the candidate contracts to enforce the project agents reach an agreement.

Moreover, Zheng *et al.* [22] proposed a critical chain-based elimination mechanism, where the project agents provided the information of activities for the coordination agent so that the activities in the critical chain were prioritized to get resource allocation. Wauters *et al.* [23] described a simple sequence learning game concerning multiple project agents and a mediator Preference information of each project agent was shared amongst the agents and the mediator scheduled the multi-project centralized based on the corresponding activity lists determined by the project agents. Li & Xu[24] developed a sequential game-based mechanism (SGM) in their two-stage decomposition approach. In the first stage, the project agents generated an initial local schedule using a meta-heuristic algorithm. In the second stage, the sequential game-based negotiation mechanism was employed to coordinate global resource conflicts.

Furthermore, Homberger & Fink [25] developed a generic negotiation mechanism with the side payments process to solve DRCMPSP with two agents. In each round of the negotiation process, a new solution was generated by a random procedure. The two agents then evaluated the new solution and voted to decide whether or not the new solution should substitute the tentative one. The strategic behaviours of the agents in the negotiation are also discussed and the reasonable strategy choice was analyzed using computational experiments.

As it is seen in the above research works, various approaches were proposed for the DRCMPSP without uncertainty. The uncertainty in a single project (or centralized multi-project) scheduling problem has been also widely studied. Methods generating robust schemes are classified as proactive scheduling and proactive scheduling for RCPSP, see, e.g., [26]–[29]. Reactive scheduling methods reduce the temporary occurrence in the process of project execution to a certain extent. They use the repairing or re-optimizing original scheduling scheme and reactively schedule the RCPSP, see, e.g., [30], [31]. For the stochastic RCPSP (SRCPSP), see, e.g., [32], [33].

Most of the existing methods for uncertainty in RCPSP do not apply to the DRCMPSP due to its distributed management environment. Only a few pieces of research dealt with the uncertainty in the distributed RCMPSP. For instance, Song *et al.* [34] assumed that the uncertainty of activity duration is related to the starting time, and the fault statistics of the instruments. If the number of faulty instruments reaches a certain limit, the corresponding activity is failed. To address this issue, a reactive process was then described, where they employed the minimum Latest Finish Time (LFT) rule (calculated by CPM) to schedule the activities to generate an initial schedule. After the disruption, all affected activities were then postponed to an earliest feasible starting time. Besides, a proactive algorithm was also developed, where they generated a set of scenarios and feasible solutions and a consensus voting process for making the final decisions. In their approach, the agents were fully collaborative. This method has been successfully applied on an instance including five projects with a total of 30 activities. Tosselli *et al.* [10] proposed a repeated-negotiation game approach to (re)scheduling the DMPSP. In their iterative and auction-based processes, the agents either act as auctioneers or bidders. Bilateral contracts were also created via a repeated negotiation game and integrated into the project plans. Any changes in the availability of resources or in the activities' durations were also considered in their case study, i.e., a pharmaceutical product development problem with 16 activities.

Our review of the literature shows that only limited research is available on the DRCMPSP with uncertain duration, especially for practical applications with reasonably large size. Our work presented in this paper aims to fill this gap by developing a multi-PR based heuristic approach for enabling efficient global resources allocation for medium and large size problems. Additionally, most of the existing researches are subject to truthful and consistent strategic agents' behaviour. In practice, however, the agents may act opportunistically, hence the above assumptions become invalid. This may significantly affect the effectiveness of coordination mechanisms. Such cases however have not been thoroughly investigated in the existing research works. In this paper, for a problem including two agents, we design a payment negotiation procedure combined with the MPR-H to address the issue of opportunistic behaviour.

III. PROBLEM DESCRIPTION

In the considered DRCMPSP with uncertain duration, multiple projects share limited global resources where the activity duration of each project is subject to a probability distribution. Individual project agent makes scheduling decisions independently to minimize the expected project tardiness cost. The objective of the DRCMPSP with uncertain duration is to determine a scheduling policy that minimizes the expected total tardiness cost, while the precedence constraints among activities and the global resource constraints are all satisfied. In our formulation we use the following parameters/variables:

- i ($i = 1, 2, \ldots, m$) is the index number of projects, rel_i indicates the earliest start time of project i [35].

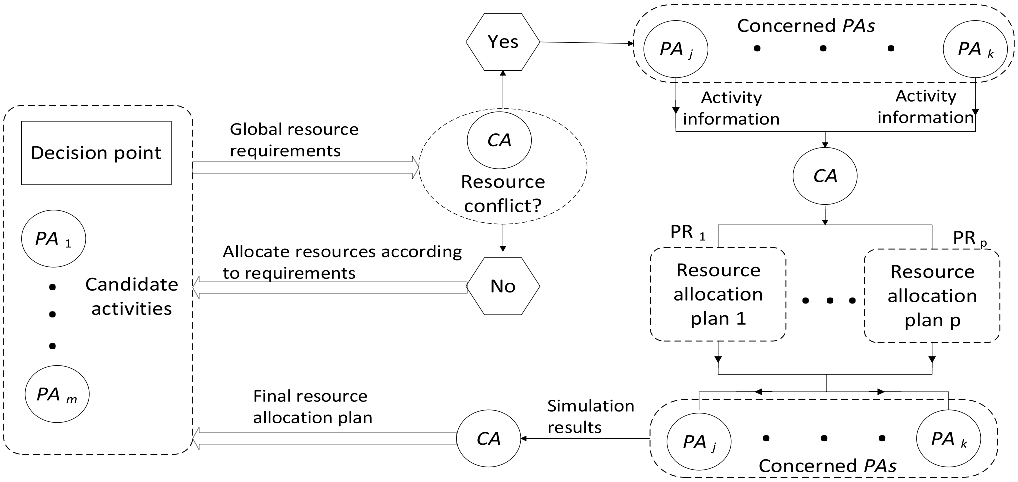

FIGURE 1. Multi-PR heuristic framework at a decision point.

- a_{ij} is the jth ($j = 1, 2, \ldots, J_i$) activity in the project i. There are J_i non-preemptable and non-dummy activities in each project i. Activities a_{i0} and $a_{i(J_i+1)}$ are dummy activities added to project i illustrating the start and the end of project i, respectively.
- The duration of activity a_{ij} is a random variable d_{ij} that follows a probability distribution. E_{ij} represents the predecessor activity set of a_{ij}, and a_{ij} cannot start before the maximal finish time of the activities in E_{ij}.
- G is the set of global (shared) resources. There are s types of global resource and global resource $g \in G$ is available with capacity R_g. Executing activity a_{ij}requires r_{ij}^g units of global resources g, $g \in G$. Dummy activities require no resources.
- T is the whole planning horizon representing the upper bound of all project completion times and $t(t = 0, 1, 2 \ldots, T)$ is the index for the point on the time axis.
- $PA = \{PA_1, PA_2, \ldots, PA_\mathrm{m}\}$ is the set of project agents. The objective of a project agent, PA_i, is to minimize the expected project tardiness cost ($EPTC$) for the project i:

$$\min \ \mathrm{E}\left(\left(s_{i(J_i+1)} - rel_i - cpl_i\right) \cdot \omega_i\right), \quad i = 1, 2, \ldots, m, \tag{1}$$

where $s_{i(J_i+1)}$ denotes the start time of activity $a_{i(J_i+1)}$, cpl_i is the critical path length of project i, ω_i is the unit project tardiness cost, and $(S_{i(J_i+1)} - rel_i - cpl_i)$ denotes the project delay. We also assume that the due date of project i is $(rel_i + cpl_i)$.
- CA is the coordinator agent responsible for allocating global resources and maximizing social welfare. The global objective is minimizing the expected total tardiness cost ($ETTC$) of the multi-project:

$$\min \ \mathrm{E}\left(\sum_{i=1}^{m} \left(s_{i(J_i+1)} - rel_i - cpl_i\right) \cdot \omega_i\right). \tag{2}$$

IV. MULTI-PR HEURISTIC APPROACH FOR DRCMPSP-UD

A decision point is a time when an activity is finished or a new project is released. For deterministic DRCMPSP, the existing research works often coordinate the global resource conflicts among the local plans. To solve DRCMPSP with uncertain duration, here, we aim at devising a resource allocation policy to dynamically coordinate the global resource conflicts at each decision point. Priority rule heuristics are extensively used in the project scheduling problems as they are fast and intuitive [33]. Based on the characteristics of the proposed problem, we develop new PRs, and to improve the basic PR heuristic we design a multi-PR heuristic. Similar to the existing research works, we start with assuming truthful behaviour and design a multi-PR based heuristic (MPR-H) approach to solve DRCMPSP with uncertain duration without limitation on the problem size. Taking consideration of the opportunistic behaviour of self-interested agents, we then describe a payment negotiation procedure which is embedded in MPR-H for the cases of problems with two agents.

A. THE FRAMEWORK OF MPR-H

Fig. 1 displays the resource allocation process at a certain decision point by the multi-PR based heuristic. At each decision point, for each project, the candidate activities are decided by the respective PA according to the precedence constraints. Then, the CA calculates the consumed amount r_e^g of global resource, g, by the candidate and ongoing activities at the current decision point (denoted as t_e). If $r_{ij}^g \leq R_g$, t_e is not a conflict time and the CA allocates the global resource g according to PAs' resource requirements and moves on to the next decision point, $t_e = t_e + 1$. Otherwise, the current time is a conflict time and the activities starting at the conflict time are conflict activities. In such cases, the concerned PAs disclose some specific information on the conflict activities to the CA. The CA then generates multiple resource allocation plans according to different PR heuristics. Resource allocation plans denoted as S_p $(p = 1, 2, \ldots P)$, are the sets of start times of the conflict activities satisfying global resource constraints. For each plan, S_p, the concerned PA_k simulates the start time of the subsequence activities with the expected duration and obtains the corresponding project makespan, and calculates the tardiness cost as:

$$tc_k^p = \left(S_{k(J_k+1)}^p - rel_k - cpl_k\right) \cdot \omega_i. \tag{3}$$

TABLE 1. Priority rules for scheduling conflict activities

Priority rule	Formula	Extreme
LFT*	$s_{ij} + d_{ij} + sl_{ij}$	Max
LST*	$s_{ij} + sl_{ij}$	Max
SD	$d_{ij} / sumd + sl_{ij}^{\sim} / sumsl^{\sim}$	Min

The CA also calculates the total tardiness cost (TTC) for each plan $TTC^p = \sum_k tc_k^p$, and selects the plan with a minimum TTC^p as the final resource allocation plan at t_e and moves on to the next decision point. The entire procedure is terminated upon scheduling of all activities.

B. THE PROPOSED PR IN MPR-H

Table 1 shows the priority rules that we proposed to schedule the candidate activities, where s_{ij} is the start time of conflict activity a_{ij}, d_{ij} is the expected duration, and sl_{ij} represents the total slack time of a_{ij}. As displayed in Table 1, PRs LFT* and LST* are similar to the classic PRs LFT (latest finish time) and LST (latest start time). In the classic PR (LFT or LST), the total slack time and start time of all activities are calculated based on the critical path method (CPM). In our proposed technique, LFT* and LST*, the start time of conflict activities equals to t_e (current conflict time) and sl_{ij} is obtained based on the current known information. At time t_e, the start time and actual duration of the activities in C_e (the set of the completed activities) are known. The pseudo-code of total slack time based on the current known information is as presented in the following.

Total Slack Time Based on the Known Information

For each concerned project:

Input: completed activity set C_e, unscheduled activity set U_e., start time and duration of $\boldsymbol{a_{ij}} \in \boldsymbol{C_e}$.

Step 1. Schedule $\boldsymbol{a_{ij}} \in \boldsymbol{U_e}$ by CPM with the expected duration. Record the start time as the earliest start time $\boldsymbol{est_{ij}}$.

Step 2. Arrange activities in descending order of completion time as priority list PL.

Backward schedule activities based on the priority list PL, where $\boldsymbol{a_{ij}} \in \boldsymbol{C_e}$ uses the actual duration and $\boldsymbol{a_{ij}} \in \boldsymbol{U_e}$ uses the expected duration. Record the start time as the latest start time $\boldsymbol{lst_{ij}}$.

Output: $\boldsymbol{sl_{ij} = lst_{ij} - est_{ij}}$.

SD is a newly proposed priority rule, where S represents the slack time and D stands for the duration. Assuming that CA_e is the set of conflict activities at current time t_e:

$$sumd = \sum_{a_{ij} \in CA_e} d_{ij} \tag{4}$$

$$sl_{ij}^{\sim} = \sum_{a_{lk} \in CA_e, a_{lk} \neq a_{ij}} -sl_{lk} \tag{5}$$

$$sumsl = \sum_{a_{ij} \in CA_e} sl_{ij}^{\sim} \tag{6}$$

In the SD rule, $d_{ij} / sumd$ is the ratio of the activity duration to the sum of all candidate activity durations. $sl_{ij}^{\sim}$ represents the opposite of the sum of the total slack times of other activities in the set of candidate activities, and $sumsl$ is the summation of $sl_{ij}^{\sim}$. Thus, SD is related to the expected duration and the total slack time of the conflict activities (obtained based on the current known information), where activities with a relatively short duration and a relatively small total slack time might start with a higher priority. The pseudo-code of our MPR-H with LLS rule (LFT* + LST* + SD) is presented in the following.

C. MULTI-PR HEURISTIC WITH PAYMENT NEGOTIATION FOR TWO AGENTS

Here we also consider opportunistic agents. Since some scheduling information is required during the coordination of global resource conflicts, self-interested agents might disclose false total slack time for the conflict activities, false simulation tardiness cost of resource allocation plans, etc. This enables them to pursue their opportunistic objectives. For multi-project with two agents, we propose a payment negotiation procedure embedded in the MPR-H and discuss the agents' strategic behaviour.

If the completion time is later than the due date, a fixed cost ω_i is paid for each the delay per unit of time, and the same cost is saved if the project is finished earlier per unit of time. We further assume that transferring money is allowed among the projects. Agents assess the schedules and propose changes to resource allocation plans in terms of their monetary values.

Following step 2 in Algorithm 1, the two PAs receive three allocation plans obtained by LFT*, LST*, and SD, respectively. Each PA ranks the plans according to the tc_k^p in ascending order and reports the rank to the CA. The CA then obtains the Pareto optimal solution (see, Fig. 2). In Fig. 2, we illustrate an example where the tardiness costs (tc) and the ranks of the plans obtained by LST*, LFT* and SD are displayed. LST* is dominated by LFT* since the tc of LFT* is lower than that of LST* from the perspective of both PAs. Moreover, there is no dominant relationship between the plans obtained by LFT* and SD. Therefore, the plans achieved by LFT* and SD are Pareto optimal solutions.

PS is the set of Pareto optimal solutions. If there is only one solution in PS, the CA allocates resources based on this plan. Otherwise, the order of the elements in PS is set per the order of the solution ranked by the PA_1. The CA determines the first solution in PS as the current optimal solution. Then PA_1 and PA_2 negotiate and decide whether to replace the current optimal solution with the next solution in PS. Due to the order of the solutions, from the first solution to the second solution in PS, the tardiness cost of PA_1 is decreased by tc_1 and the delay cost of PA_2 is increased by tc_2. PA_1 asks for tc_1 in compensation to agree with the second solution. If $tc_2 > tc_1$, PA_2 pays for the cost and the second solution becomes the current best solution. Otherwise, they continue to negotiate the third Pareto solution until all Pareto

PA_1	*tc*	Rank	PA_2	*tc*	Rank
LFT*	15	2	LFT*	21	1
LST*	19	3	LST*	25	2
SD	13	1	SD	27	3

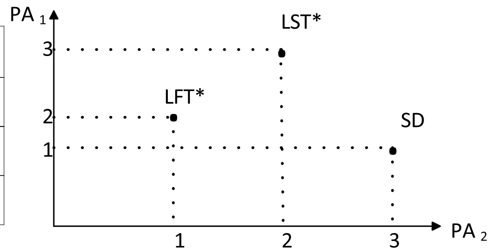

FIGURE 2. An example of Pareto solutions.

Algorithm 1 MPR-H With LLS (LFT* + LST* + SD)

Initialize: decision point $t_e = 0$, unscheduled activity set $UA_{e.} = \{\text{all activities}\}$.

Step 1. *While* $UA_{e.} \neq \emptyset$ *do*
Each PA determines candidate activities.
CA calculates r_e^g.
If $r_e^g \leq R_g$
CA allocates resources as required, then updates t_e and UA_e.
Continue.
Else
Go to step 2.
End if.
End while.

Step 2. PA calculates the total slack time sl_{ij} of each conflict activity.
PA submits d_{ij} and sl_{ij} to CA.
CA determines three resource allocation plans according to LFT*, LST* and SD.
CA schedules the conflict activities according to LFT*/LST*/SD and PSGS (parallel schedule generator scheme), resulting in three resource allocation plans (S_1, S_2, S_3). CA provides the resource allocation plans for concerned PAs.
Go to step 3.

Step 3. *For* $p = 1{:}3$
For each concerned PA_k:
Simulate the start time of subsequence activities using expected duration based on a resource allocation plan S_p.
Record $s^p_{k(J_k+1)}$ and calculate tc^p_k as (3).
End for
CA calculates the score of each plan $TTC^p = \sum_k tc^p_k$.
Final resource allocation plan $S_f = \min_{p=1,2,3} (TTC^p)$.
CA allocates resources as S_f.
Update t_e and UA_e.
Go to **step 1**.

Algorithm 2 MPR-H With Payment Negotiation for Two Agents

Initialize: decision point $t_e = 0$, unscheduled activity set $UA_{e.} = \{\text{all activities}\}$.

Step 1 & Step 2we refer to **Algorithm 1**.
Go to **step 3.**

Step 3. *For* $p = 1 : 3$
For each concerned PA_k:
Simulate the start time of subsequence activities using expected duration based on a resource allocation plan S_p.
Record $s^p_{k(J_k+1)}$ and calculate tc^p_k as (3).
End for
Each PA ranks the plans according to the $\boldsymbol{tc^p_k}$ in ascending order, based on which CA determines the Pareto set *PS*.
If $|PS| = 1(|PS|$ is the number of the elements in *PS*)
CA allocates resources as the current optimal solution.
Else
for $p = 2 : |PS|$
Agents negotiate whether replace the current optimal solution with the *p*th element in *PS*.
PA_1 calculates the difference in the tardiness cost between the two solutions: tc^p_1.
PA_2 calculates the difference in the tardiness cost between the two solutions: tc^p_2.
If $tc^p_2 \geq tc^p_1$
replace the current optimal solution with the *p*th solution.
Else
Continue.
End if.
End for.
CA allocates resources as the final optimal solution.
End if.
Update t_e and UA_e.
Go to **step 1.**

solutions are discussed. The CA allocates the resources to PA as the final solution obtained by the above negotiation, then steps to the next decision point. The pseudo-code of the MPR-H with payment negotiation for two agents is as the following.

In our MPR-H with payment negotiation for two agents, an opportunistic agent may behave untruthful, such as submitting false total slack time, untruthful solution ranks, etc. The total slack time represents the urgency of activity in

TABLE 2. Problem instances of RCMPSP

Problem subset	*NOI*	Characterization per instance				*AUF*
		m	J_i	Problem Size	|G|	
MP30_2	5	2	30	60	1, 2 or 3	0.84
MP90_2	5	2	90	180	1, 2 or 3	0.57
MP120_2	5	2	120	240	1, 2 or 3	1.31
MP30_5	5	5	30	150	1, 2 or 3	0.82
MP90_5	5	5	90	450	1, 2 or 3	0.61
MP120_5	5	5	120	600	1, 2 or 3	1.32
MP30_10	5	10	30	300	1, 2 or 3	2.38
MP90_10	5	10	90	900	1, 2 or 3	1.14
MP120_10	5	10	120	1200	1, 2 or 3	1.91
MP30_20	5	20	30	600	1, 2 or 3	3.37
MP90_20	5	20	90	1800	1, 2 or 3	0.90
MP120_20	5	20	120	2400	1, 2 or 3	0.87
MP90_2AC	10	2	90	180	4	2.27
MP120_2AC	10	2	120	240	4	1.36
MP90_5AC	10	5	90	450	4	4.99
MP120_5AC	10	5	120	600	4	3.80
MP90_10AC	10	10	90	900	4	3.85
MP120_10AC	10	10	120	1200	4	2.61
MP90_20AC	10	20	90	1800	4	2.20
MP120_20AC	10	20	120	2400	4	3.65

a project. Therefore, a self-interested agent may submit a false total slack time which is smaller than its real value. For the solution rank, there is no plausible advantage by deviating from the truthful behaviour. This is because an agent with untruthful behaviour may miss an advantageous solution. For the negotiation of Pareto solutions, an agent with untruthful behaviour may lose earnings or miss a better solution as well. In Section 5 we analyze the strategic behaviour of submitting a false total slack time and provide insights on the effectiveness of different behavioural choices, and note that the payments between the agents do not affect the global objective since the total tardiness cost is the summation of the tardiness costs of all the projects.

V. COMPUTATIONAL STUDY

The performance of our MPR-H is evaluated via a comprehensive computational experiment in this section. All experiments are performed on a PC with 3.4GHz CPU and 8GB RAM, and the algorithms are coded in Matlab 2013a. In Subsection *A*, we provide the experimental design in details including the instance sets, parameters, and duration distributions. The performance of different multi-PRs is analyzed in Subsection *B*. The effect of problem characteristics on the objective is reported in Subsection *C*. In Subsection *D* we compare the performance of our MPR-H to competitive distributed/centralized algorithms. The strategic behavior of agents is analyzed in Subsection *E*.

A. EXPERIMENTAL SETUP

We tested our approach on MPSPLIB [13] datasets shown in Table 2. The MPSPLIB problem library includes 140 instances. All these instances are available on a public web site http://www.mpsplib.com (last check of address: 12 November, 2020). Each problem subset is named as "MPJ_i_m" or "MPJ_i_mAC", where J_i is the number of non-dummy activities in each project and m is the number of projects in each instance. Other parameters are illustrated as follows: *NOI* is the number of instances in each subset and the problem size is the total number of non-dummy activities per instance, $|G|$ is the number of global resources, *AUF* is the average of the *UF* in a certain problem subset, and *UF* denotes the maximal tightness of the constraints on the required shared resources as in (7) [36]. In our experiment, UF_g is the ratio of the total amount of required g to the constant amount capacity of g in each period over the critical path length of the multi-project (see, [21] for more details).

$$UF = \max_{g \in G} UF_g \tag{7}$$

According to [37], the threshold of UF is 1. If $UF < 1$, the instance resource conflict is relatively low, and vice versa. Here, we focus on the allocation of the scarce shared resources. Thus for the resource constraints, only global resource constraints are considered. We then follow [38] and [39], in line with their probability distribution types and parameters. For each distribution type, the expected activity duration is equal to the original activity duration in the MPSPLIB data sets. Five distributions and their variances are also shown as follows:

(1) U1: subject to uniform distribution, support $\left[d_{ij}^* - \sqrt{d_{ij}^*}, d_{ij}^* + \sqrt{d_{ij}^*}\right]$, variance $d_{ij}^* \big/ 3$;
(2) U2: subject to uniform distribution, support $\left[0, 2d_{ij}^*\right]$, variance $d_{ij}^{*2} \big/ 3$;
(3) EXP: subject to exponential distribution, mean d_{ij}^*, variance d_{ij}^{*2};
(4) B1: subject to beta distribution, support $\left[d_{ij}^* \big/ 2, 2d_{ij}^*\right]$; variance $d_{ij}^* \big/ 3$, shape parameter $\alpha = d_{ij}^* \big/ 2 - 1 \big/ 3$, $\beta = 2\alpha$;
(5) B2: subject to beta distribution, support $\left[d_{ij}^* \big/ 2, 2d_{ij}^*\right]$; variance$d_{ij}^{*2} \big/ 3$, shape parameter $\alpha = 1 \big/ 6$, $\beta = 2\alpha$.

As it is seen, U1 and B1 have a relatively low variance, U2 and B2 have medium variance, and EXP has a high variance. All results in the following parts are the average of 100 runs. All the distribution sampling functions denoted as *randperm*. *expinv* and *betainv* in our experiment came from Matlab 2013a.

B. PERFORMANCE OF DIFFERENT MULTI-PR HEURISTICS IN MPR-H

The multi-PR mainly determines the performance of our MPR-H approach. We compare four different multi-PRs, which are different combinations of the PRs in Table 1 on the test sets under different distributions. In Table 3, the average *ETTC* results for each subset under U1 distribution and the average running time of each run are presented. The best results are also marked in bold. The LLS rule outperforms other multi-PRs on 17 of the 20 problem subsets. For all other distributions, the above setting remains unchanged.

TABLE 3. Comparison of different multi-PR combinations in MPR-H

Problem subset	LLS		LFT*&LST*		LFT*&SD		LST*&SD	
	ETTC	CPU (s)	*ETTC*	CPU (s)	*ETTC*	CPU (s)	*ETTC*	CPU (s)
MP30_2	93.82	0.188	130.19	0.184	94.65	0.183	**86.35**	0.175
MP90_2	106.00	0.346	75.89	0.331	**73.64**	0.320	139.13	0.322
MP120_2	**574.47**	0.617	705.89	0.616	625.73	0.610	652.21	0.594
MP30_5	**355.25**	0.462	431.40	0.468	362.76	0.448	405.79	0.457
MP90_5	**662.39**	1.023	947.51	0.974	763.53	0.970	707.32	0.965
MP120_5	**2789.34**	1.960	2954.21	1.799	3019.17	1.809	3081.71	1.895
MP30_10	**705.11**	1.224	811.31	1.101	786.56	1.112	778.91	1.169
MP90_10	**3064.72**	3.177	3541.96	3.046	3429.58	3.094	3301.50	2.985
MP120_10	**4500.86**	4.246	4854.47	4.124	4656.82	4.049	4607.63	4.128
MP30_20	**2117.78**	2.560	2164.86	2.569	2196.95	2.456	2175.58	2.438
MP90_20	**5001.40**	5.271	5389.33	4.769	5093.07	4.861	5172.37	4.925
MP120_20	**9604.25**	7.635	10161.34	7.346	10327.36	7.515	10567.57	7.510
MP90_2AC	260.30	0.459	390.84	0.475	**248.18**	0.472	257.97	0.455
MP120_2AC	**224.68**	0.580	296.65	0.545	247.54	0.531	232.46	0.537
MP90_5AC	**1427.83**	1.746	1508.12	1.592	1527.48	1.578	1578.43	1.637
MP120_5AC	**4011.57**	2.414	4251.63	2.330	4319.30	2.352	4397.50	2.294
MP90_10AC	**2940.58**	3.467	2986.47	3.247	3089.61	3.337	3127.07	3.261
MP120_10AC	**6657.06**	4.608	6857.76	4.445	6813.08	4.368	6862.68	4.430
MP90_20AC	**5226.79**	5.959	5940.94	5.674	5701.72	5.767	5539.24	5.802
MP120_20AC	**15849.46**	10.382	16513.11	10.046	16487.12	9.662	16532.32	9.897

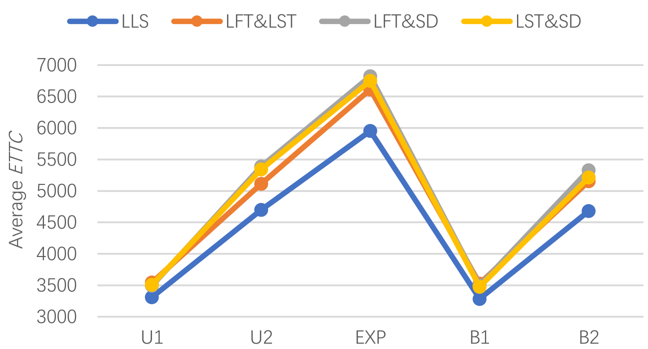

FIGURE 3. The average ETTC of different multi-PRs under different distribution.

Besides, for each multi-PR, the average running time is within 11 seconds.

Fig. 3 shows the average *ETTC* of the test sets for each multi-PR under different distributions. To test the significance of the results in Fig. 3, we conduct 2-tailed Wilcoxon signed-rank test on each pair of multi-PRs (neither the results of each multi-PR nor the differences between pairs are normally distributed, so we do not apply Student's t-test or paired t-test). Table 4 shows the confidence levels for each pair of multi-PRs under different activity duration distributions. Italic entries indicate that there is a significant difference between the two multi-PRs at the 1%-level of significance. It is observed from Fig. 3 and Table 4, the LLS rule significantly outperforms other multi-PRs under all distributions.

TABLE 4. 2-talied Wilcoxon signed-rank results for the multi-PRs

Distribution	multi-PR	LFT*&LST*	LFT*&SD	LST*&SD
U1	LLS	*0.000*	*0.000*	*0.000*
	LFT*&LST*		0.048	0.391
	LFT*&SD			0.191
U2	LLS	*0.001*	*0.001*	*0.001*
	LFT*&LST*		*0.006*	0.108
	LFT*&SD			0.218
EXP	LLS	*0.001*	*0.000*	*0.006*
	LFT*&LST*		*0.000*	0.737
	LFT*&SD			*0.000*
B1	LLS	*0.000*	*0.000*	*0.001*
	LFT*&LST*		0.370	0.167
	LFT*&SD			0.332
B2	LLS	*0.001*	*0.002*	*0.005*
	LFT*&LST*		0.086	0.823
	LFT*&SD			0.015

It is also seen that the LLS multi-PR is the most efficient PR for our MPR-H.

C. THE EFFECT OF PROBLEM CHARACTERISTICS

Fig. 4 displays the average *ETTC* of the MPR-H with LLS rule under different variances and *AUF* values. The results of low (medium) variance are the average of the results where the activity duration distributions are U1 and B1 (U2 and B2).

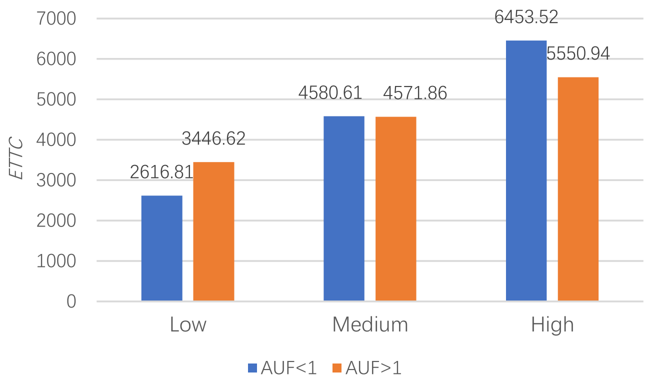

FIGURE 4. ETTC under different problem parameters.

Furthermore, the high variance results are from the EXP distribution. The variance represents the degree of uncertainty, and the *AUF* value represents the strength of global resource conflicts. It is also seen in Fig. 4 that the *ETTC* increases with the degree of uncertainty. However, only in the case of low uncertainty, the *ETTC* increases with the value of *AUF*. In the case of medium certainty, the *ETTC* of different resource conflicts are similar. For the cases with high uncertainty, the result is against what it is usually expected.

This is because the multi-projects with low *AUF* are more affected by the change of uncertainty. To show this effect, we illustrate the ratio of high uncertainty results in low uncertainty results of different *AUF* in Fig. 5. In Fig. 5(a), for instance, the MP90_2 data point of "AC" is the ratio of the *ETTC* under EXP distribution to the average *ETTC* under U1 and B1 distribution for MP90_2AC subset. "NAC" represents the results of MPJ_i_m subsets.

From Table 2, for the same problem size, the MPJ_i_mAC subsets have higher *AUF* than that of the MPJ_i_m subsets. Except for the data points at MP120120_2, all results show that the *ETTC* is more affected by the uncertainty on low *AUF*. The *AUF* values of the MP120_2AC subset and the MP120_2 subset are almost the same (1.36 & 1.31), which might be the reason for the above result.

Moreover, we calculate the ratio of high uncertainty results in low uncertainty results for the average results of all problem subsets of $AUF < 1$ and $AUF > 1$ in Fig. 5(b). The results in Fig. 5 illustrate that for the problem subset with $AUF < 1$, the *ETTC* result under EXP distribution is 5.06 times higher than that of the average *ETTC* under U1 and B1 distributions. For $AUF > 1$, the ratio is 2.17.

The above analysis suggests that the *ETTC* is increased by increasing the uncertainty. The *ETTC* also increases more where $AUF < 1$ and less where $AUF > 1$.

D. A COMPARISON WITH DISTRIBUTED/CENTRALIZED ALGORITHMS

To be able to evaluate the performance of MPR-H, we compare our approach with two competitive decentralized algorithms for deterministic DRCMPSP [22], [24], and the best four priority rules (LFT, LST, SLFT, and SLST) for the stochastic RCPSP (SRCPSP) verified by Chen *et al.* [33]. We introduce the algorithms briefly as follows:

- DMAS/EM: A distributed method for deterministic DRCMPSP. In this algorithm, the conflict activities are scheduled in the order of the ascending scores and the score of each activity is calculated as $M * Sl_i + d_i$, where M is a large enough constant, Sl_i represents the slack time of conflict activity i and d_i is its duration [22]. We use the expected activity duration to calculate the above parameters.
- SQM: Sequential game is based on two-stage decomposition algorithm for deterministic DRCMPSP. In SQM, the global resources are allocated in the project level. The project orders are then evaluated [24] and the evaluation of the order of each project is carried out with the expected activity duration as defined in this paper.
- LFT and LST: Two centralized methods; efficient priority rules for SRCPSP; the latest finishing time and the latest starting time, are respectively calculated by the expected activity durations [33].
- SLFT and SLST: Two centralized methods; efficient priority rules for SRCPSP; the simulation-based latest finishing time and the simulation-based latest starting time, are respectively calculated by the average of n times simulations, and in each simulation, the simulated activity duration is used instead of the expected activity duration [33].

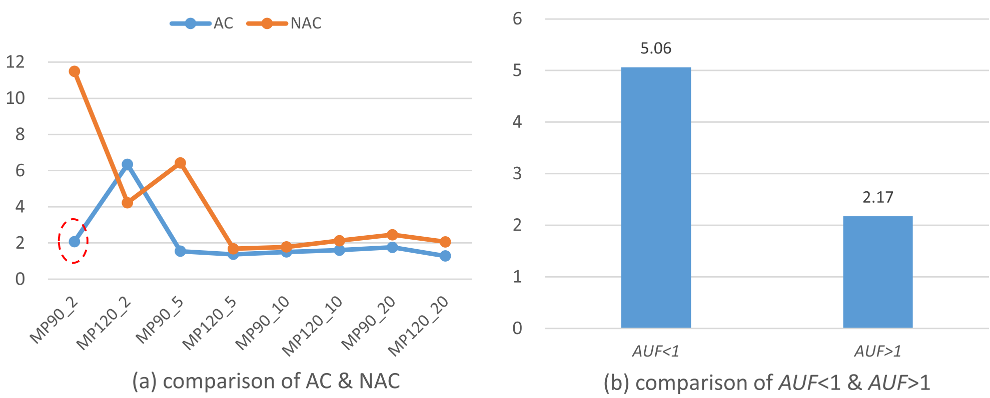

FIGURE 5. The effect of AUF on the results of different variance.

TABLE 5. Comparison between MPR-H and other algorithms

Problem subset	LLS	DMAS/EM	LFT	LST	SGM	SLFT	SLST
mp_2j30	5.73	**5.55**	10.36	9.11	9.87	10.05	9.62
mp_2j90	**2.16**	3.02	3.35	3.63	7.81	3.99	2.93
mp_2j120	**7.30**	9.10	9.06	9.37	15.42	9.85	10.26
mp_5j30	**20.10**	23.98	24.95	25.86	23.26	27.27	27.29
mp_5j90	**15.64**	21.25	21.21	19.03	16.32	20.48	19.64
mp_5j120	**46.91**	50.28	50.08	51.04	51.62	52.65	53.29
mp_10j30	**58.08**	67.97	66.63	67.40	66.25	70.38	66.64
mp_10j90	**86.72**	100.56	97.09	98.25	93.24	102.65	105.97
mp_10j120	**75.62**	81.82	81.44	80.29	81.82	93.20	89.87
mp_20j30	**141.58**	149.11	146.49	149.15	168.83	157.78	162.36
mp_20j90	**113.53**	126.34	126.60	120.90	122.52	140.84	138.87
mp_20j120	158.09	164.28	164.42	166.15	**157.70**	176.77	180.93
mp_2j90AC	**7.03**	8.47	8.76	7.11	165.70	10.89	11.20
mp_2j120AC	**4.15**	4.60	5.67	5.46	45.46	7.59	7.12
mp_5j90AC	**51.34**	58.14	56.40	57.82	66.36	63.75	61.32
mp_5j120AC	**56.01**	60.36	57.50	60.23	66.67	65.26	64.52
mp_10j90AC	90.41	94.37	**88.30**	95.78	108.34	111.55	109.58
mp_10j120AC	**102.21**	106.88	109.80	106.18	109.18	116.37	116.94
mp_20j90AC	**164.90**	187.12	196.60	188.40	185.30	209.49	207.73
mp_20j120AC	**236.62**	246.58	255.60	247.14	262.70	274.61	271.52

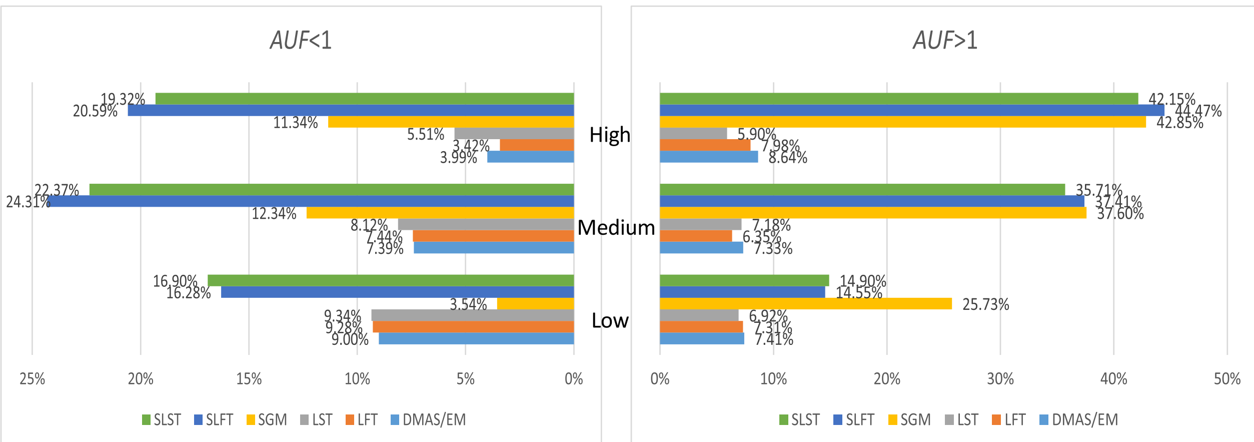

FIGURE 6. Percentage improvement with respect to different problem parameters.

Five of the above six algorithms are time-oriented, designed to minimize the average project delay or expected project makespan. The SQM, which aims at minimizing the total tardiness cost can solve the deterministic DRCMPSP with any unit tardiness cost. Therefore, in this subsection, the unit tardiness cost of each project is set as 1. The *ETTC* is consistent with the expected total project delay (*ETPD*) which is calculated as:

$$ETPD_i = \mathrm{E}\left(\sum_{i=1}^{m} (s_{i(J_i+1)} - rel_i - cpl_i)\right) \tag{8}$$

The average results of *ETPD* under U1 distribution are shown in Table 5. The optimal results are marked in bold.

As it is seen in Table 5, our MPR-H with LLS rule outperforms other algorithms in 17 of the 20 problem subsets. For the B1 and EXP distributions, the above conclusion remains unchanged, and for the U2 and B2 distributions, our approach outperforms other algorithms in 19 of the 20 problem subsets. Fig. 6 shows the average percentage improvement of our MPR-H compared to other algorithms under different values of the variances and *AUF*. It is can be observed that our MPR-H achieves significant improvements for all situations.

E. ANALYSIS OF THE STRATEGIC BEHAVIOR

In this subsection, we analyze whether or not lying is advantageous in the process of information exchange for the two

TABLE 6. Objective value for different strategic behavior

Distribution	agent	Both agents truthful	PA_1 lies with p=0.5	PA_2 lies with p=0.5	Both agents lie with p=0.5
U1	PA_1	101.34	119.29	119.60	90.57
	PA_2	150.52	178.90	168.83	192.99
	CA	251.85	298.19	288.43	283.57
U2	PA_1	388.79	391.60	366.53	408.97
	PA_2	433.13	454.60	478.55	470.08
	CA	821.92	846.20	845.08	879.05
EXP	PA_1	543.44	654.05	553.20	619.66
	PA_2	658.60	631.24	683.11	723.77
	CA	1202.04	1285.29	1236.31	1343.43
B1	PA_1	93.61	115.66	117.40	107.38
	PA_2	162.86	181.39	174.20	169.60
	CA	256.47	297.05	291.60	276.98
B2	PA_1	353.12	427.47	365.61	365.08
	PA_2	478.26	437.12	501.40	470.91
	CA	831.38	864.59	867.01	835.99

TABLE 7. Expected *EPTC* under different behavior for U1 distribution

EPTC (PA1, PA2)	PA2 truthful	PA2 lies
PA1 truthful	(101.34, 150.52)	(119.60, 168.83)
PA1 lies	(119.29, 178.90)	(90.57, 192.99)

agents and the strategy is chosen by a self-interested agent? As it was discussed in Section 4, an opportunistic agent might provide a false total slack time which is smaller than the actual one. Each of the PAs might select to behave truthfully or untruthfully. We study this strategy selection question in detail for the problem subsets with two projects (MP30_2, MP90_2, MP120_2, MP90_2AC, and MP120_2AC) under five activity duration distributions.

The average results of the five subsets are shown in Table 6. An agent with truthful behaviour provides the true total slack time to the CA, and a lying agent tampers the total slack time and changes it to 0 with a probability of 0.5. The rows of PA_1 and PA_2 are the average results of the tardiness cost for the two projects, respectively, and the row of CA is the average results of *ETTC* for the multi-project.

To demonstrate the results of different strategy selections, we display the situation of U1 distribution in Table 7. It is can be seen in Table 7 that from the perspective of a rational PA_2, the best strategy is to behave truthfully. This is because PA_2 achieves the better individual result (i.e., lower *ETTC*) in both cases irrespective of the strategy of PA_1 (150.52 vs. 168.83, 178.90 vs. 192.99). Therefore, the dominant strategy for PA_2 is to behave truthfully. For PA_1, when PA_2 behaves truthfully, PA_1 gets better individual result by truthful behaviour (101.34 vs. 119.29). All differences are statistically significant (Wilcoxon signed-rank test, $p < 0.01$). Individually rational behaviour leads to a dominant-strategy equilibrium (101.34, 150.52) which obtains a lower *ETTC* than that of the untruthful behaviour. Similar effects are seen for other distributions.

According to the above analysis, in our MPR-H with the payment negotiation process, untruthful behaviour commonly leads to a higher tardiness cost for the untruthful agent, whereas the agents behaving truthfully achieve high-quality solutions.

VI. CONCLUSION AND FUTURE WORK

This paper is devoted to solving the distributed multi-project scheduling problem under uncertain durations, where the activity durations are subject to a known probability distribution. We propose a multi-PR heuristic (MPR-H) approach to dynamically allocate the global resources. Three priority rules based on the current known information are proposed and embedded in the proposed heuristic algorithm. We further consider opportunistic agent and propose MPR-H with payment negotiation to counter the agents' strategic behaviour in cases with two projects. A comprehensive computational experiment on the MPSPLIB benchmark is also performed to examine the performance of our proposed algorithm and analyze the agents' strategic behaviour.

According to the computational results, the LLS rule (which is the combination of LFT*, LST*, and SD) significantly outperforms other multi-PRs for the MPR-H. Satisfactory solutions for large size and strong conflict instances can be obtained within only 11 seconds by our MPR-H with LLS. The senior manager will face complex decision situations and more *ETTC* might incur for strong uncertainty. By increasing the level of uncertainty, multi-project with relatively slack global resource constraints also leads to a higher increase in *ETTC* than the multi-project with relatively tight global resource constraints. The performance of our MPR-H is also compared with six competitive distributed/centralized algorithms. Experimental results reveal that the proposed MPR-H with LLS approach can significantly improve the solution in terms of *ETPD* under various distributions. For the problem with two agents, by analyzing the strategic behaviour of the agents, the results illustrate that the rational agents will behave truthfully, which is the dominant strategy equilibrium, and with the truthful strategies, the multi-project obtains high-quality results.

Although our work solves the two-agent problems without implying a strong assumption on the truthful behaviour, solving problems with more opportunistic agents require further effort. Furthermore, in some cases, the local resources (resource required in a single project) can be limited in the multi-project which has not been considered in the current work. Other promising priority rules might be incorporated in our MPR-H. Future research may cover the above shortcomings and incorporate our multi-PR heuristic and the new PRs in meta-heuristics (or neighbourhood search techniques) to address other scheduling problems.

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