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Bi-level optimization of resource-constrained multiple project scheduling problems in hydropower station construction under uncertainty

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Particle swarm optimization.

Abstract. The aim of this paper is to deal with Resource-Constrained Multiple Project Scheduling Problems (RCMPSP), which consider the complex hierarchical organization structure and fuzzy random environment in the decision making process. A bi-level multi-objective RCMPSP model with fuzzy random coefficients is presented, taking into account the strategy and process in the practical RCMPSP. In the model, the project director is considered the leader at the upper level who aims to minimize the total tardiness penalty of all sub-projects and the consumption of resources. Meanwhile, the sub-project manager, a follower at the lower level, regards the target to minimize the duration of each sub-project. To deal with the uncertainties, fuzzy random parameters are transformed into trapezoidal fuzzy variables first, which are subsequently de-fuzzified by the expected value index. A multi-objective bi-level adaptive particle swarm optimization algorithm (MOBL-APSO) is designed as the solution method to solve the model. The results and analysis of a case study are presented to highlight the practicality and efficiency of the proposed model and algorithm.

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1. Introduction

As the scale of projects has generally become larger in recent years, the organizational structure of activities in a large-scale construction project is also very complex. Hence, these activities are usually deemed sub-projects in practice. In this situation, Resource-Constrained Multiple Project Scheduling Problems (RCMPSP) have attracted growing attention in both theory and practice. Since Fendley first considered activities in a complex project as sub-projects, in 1968 [1], the importance and comprehensive practicality of RCMPSP have been widely accepted by project managers. Fricke and Shenhar [2] provided insight into how the most important multiple-project success factors in a manufacturing support environment differ from factors of success in traditional single-project management, by a case study method. Lova et al. [3] developed a multi-criteria heuristic that improved the criteria lexicographically, i.e. project delay or multi-project duration increase and project splitting, in-process inventory, resource leveling or idle resources. Then, in 2001, Lova and Tormos [4] analyzed the effect of schedule generation schemes, such as serial

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or parallel, and priority rules that were MINLFT, MINSLK, MAXTWK, SASP or FCFS in single and multiple project environments. Kim et al. [5] proposed a hybrid genetic algorithm with a fuzzy logic controller (flc-hGA) for RCMPSP, and demonstrated that the proposed flc-hGA yielded better results than conventional and adaptive genetic algorithms. Deng et al. [6] and Czogalla [7] used a Particle Swarm Optimization (PSO) approach to solve RCMPSP. Brucker et al. [8], Kolisch and Padman [9] Demeulemeester and Herroelen [10] reviewed the numerous project optimization scheduling problems in project management theory in [8,9,10], respectively, including RCMPSP. Recently, deeper research into RCMPSP has been undertaken by a number of researchers, such as Browning and Yassine [11], Tasan and Gen [12], Dong et al. [13], Palencia and Delgadillo 14], and so on.

In all the above literature, there is an implicit assumption that the decision-maker is unique. However, since the scale of the project is usually very large, in practice, more elements and the complex hierarchical organization structure should be considered in the scheduling process of RCMPSP. Actually, multi-level programming has been successfully applied in project scheduling problems. Chen and Tzeng [15] established a bi-level fuzzy multi-objective model to aid the reconstruction scheduling for a post-quake road network. The upper objectives were to minimize travel time, total working time, and idle time between work-troops. The lower objective was to obtain a convergent link flow under the reconstruction states of the road network from the upper level. Tan et al. [16] used a bi-level decision method to construct a mathematical model of a multi-resource constrained multi-project scheduling problem, and proposed a stochastic global optimization method, based on direct search, to solve the global optimal problem. Roghanian et al. [17] proposed a probabilistic bi-level linear multi-objective programming model to enterprise-wide supply chain planning problems, and obtained a compromised solution using a fuzzy programming technique. Peng et al. [18] constructed a bi-level model for maintenance fund allocation and project prioritization, and used dynamic programming and the genetic algorithm to solve the proposed model. Although there is little research into multi-level organizational structures in RCMPSP, application of multi-level decision-making methods in RCMPSP will become increasingly extensive and in-depth following the advances in engineering design and industry segmentation.

Another key issue worth our attention in RCMPSP is the inevitable uncertainty in the decision-making process. Generally speaking, there are two types of uncertainty in practical RCMPSP: The first is internal, such as the perception and dissension of decision makers (subjective uncertainty); the second uncertainty is caused by external factors, such as treacherous weather and equipment failure (objective uncertainty). Subjective uncertainty can be tackled using fuzziness, and objective uncertainty can be handled by randomness, respectively. Traditionally, the uncertainty of project scheduling problems is assumed to be random. In 1960, Freeman first solved the project scheduling problem using a probability theory [19]. After that, many researchers considered randomness in the scheduling process, such as activity durations [20-22], task costs [23,24], and so on. Following Prade [25], which first applied fuzzy set theory to project scheduling problems in 1979, many researchers have become devoted to Resource Constrained Project Scheduling Problems (RCPSP) under a fuzzy environment, such as Wang et al. [26], Bhaskar et al. [27], and Masmoudi and Haït [28]. Fuzziness and randomness are considered separate aspects in the above research. However, we may face a hybrid uncertain environment in practical RCMPSP. Hence, the fuzzy random variable, which was initialized by Kwakernaak [29] in 1978, can be a useful tool to deal with two kinds of uncertainty simultaneously. No attempt has been made to consider the quantity of maximum renewable resources, penalty cost coefficients, duration of sub-projects, and the processing time of activities in sub-projects as the fuzzy random variables. Therefore, there is a strong motivation and justification for this study, i.e. taking into account the complex hierarchical organizational structure and the fuzzy random environment in practical RCMPSP.

This paper will solve RCMPSP by bi-level decision-making methods, with a mixed uncertainty of fuzziness and randomness. The remainder of the paper is organized as follows. In Section 2, the research problem and statement are presented, including the explanation of the motivation behind employing fuzzy random variables. Then, a bi-level multi-objective RCMPSP model is proposed in Section 3. Details of the approach used in transforming fuzzy random variables into trapezoidal fuzzy variables are also presented, and then the expected value operator is employed to deal with the fuzzy variables. In Section 4, a Multi-Objective Bi-Level Adaptive Particle Swarm Optimization algorithm (MOBL-APSO) is utilized to resolve the RCMPSP model. The effectiveness of the proposed model and algorithm is proven by the practical application in Section 5. Concluding remarks are made in Section 6, along with discussion about further research.

2. Research problem and statement

The problem considered in this study is from the Xiangjiaba Hydropower Project, which is a large-scale water conservancy and hydropower construc-

Figure 1. The location of Xiangjiaba Hydropower Station.

tion project on the Jinsha River; a tributary of the Yangtze River in Yunnan Province and Sichuan Province (southwest of China). As the ultra-large hydropower project (the third largest hydropower project in China, second only to the three Gorges station and the Xiluodu station), Xiangjiaba Hydropower Station is a concrete gravity dam, and it is the lowest station of the Jinsha River downstream cascade development (see Figure 1). The facility of the Xiangjiaba Hydropower Station runs on eight turbines, each with a capacity of 800,000-kilowatts, totaling the generating capacity to 6,400 6,400,000-kilowatts. The height and length of the dam are 161 meters (528 ft) and 909 meters (2,982 ft), respectively. The project boasts comprehensive functions such as power generation (transmits much of the power to Shanghai), flood prevention, navigation and irrigation.

2.1. Bi-level problem description

In the Xiangjiaba Hydropower Project, the Hydrochina Zhongnan Engineering Corporation (HZEC) is the construction contractor and is in charge of operation and management, such as exploration, project scheduling design, construction site design, and so on. However, in the RCMPSP, HZEC do not undertake sub-projects, because they are typically bidden and outsourced in the large-scale construction project. In this situation, the practical RCMPSP discussed in this paper considers the construction contractor (project director) as the Upper Level Decision Maker (ULDM), while the sub-project manager is the Lower Level Decision Maker (LLDM). Moreover, the ULDM and LLDM have different goals: ULDM aims to minimize the total tardiness penalty of all sub-projects and the consumption of resources, and LLDM regards its target as minimizing the duration of each sub-project.

In the scheduling design process of the RCMPSP, the resource allocation scheme of the whole project is given by the ULDM at first. Then, LLDM assigns the resources to determine the minimum duration of sub-projects, and provides feedback of the results to the ULDM. Subsequently, ULDM adjusts the resource allocation according to the upper objective functions. The process above is repeated, until the optimal scheduling and optimal resource allocation schemes are finally obtained. This complex decision making process, with its hierarchical organizational structure is shown in Figure 2.

2.2. Motivation for employing fuzzy random variables in RCMPSP

The requirements for addressing uncertainty in project scheduling problems are widely recognized [30]. Although the probability theory has been applied to project scheduling problems successfully, sometimes it may not be suitable for RCMPSP in a new large-scale construction project because the preliminary and relevant information is more imprecise than before, due to advancements in engineering technology. For example, in order to collect the data in the Xiangjiaba Hydropower Station, some investigations and surveys are undertaken with different experienced engineers (i.e., $e = 1, 2, \cdots, E$, where e is the index of engineers). However, instead of exact parameters, the engineers can describe the parameters as an interval (i.e., $[l_e, r_e]$), with the most possible value (i.e., m_e), such as "the maximal requirement of steel is between 8.50 and 10.15 million kg, and the most possible quantity is 9.45 million kg". Because different engineers have different opinions for the parameters, the minimum value of all l_e (i.e., a) and the maximal value of all r_e (i.e., b) are selected as left and right borders, respectively. Meanwhile, by comparing the most possible values (i.e., m_e for $e = 1, 2, \cdots, E$) and using the maximum likelihood method, fluctuation of all m_e can be characterized as a stochastic normal distribution (i.e., $\phi(\omega) \sim N(\mu, \sigma^2)$). Hence, it means that the maximal requirement of steel is a fuzzy variable taking a random parameter, i.e. a fuzzy random variable $(a, \phi(\omega), b)$, where $\phi(\omega) \sim N(\mu, \sigma^2)$.

In fact, the fuzzy random variable has been successfully applied in many areas, such as project scheduling problems [31], inventory problems [32-34], vehicle routing optimization problems [35], portfolio selection problems [36-39], and so on. The research mentioned above proves that the fuzzy random variables can effectively deal with a hybrid uncertain environment, where fuzziness and randomness co-exist. In this paper, the fuzzy random variable is also employed to characterize the complexity of the uncertain environment in the practical RCMPSP. The reason why the maximal requirement of steel is a triangular fuzzy random variable is shown in Figure 3.

Similarly, while modeling the RCMPSP in Xiangjiaba Hydropower Station under the fuzzy random environment, the quantity of maximum renewable resources, the penalty cost coefficients, the duration of

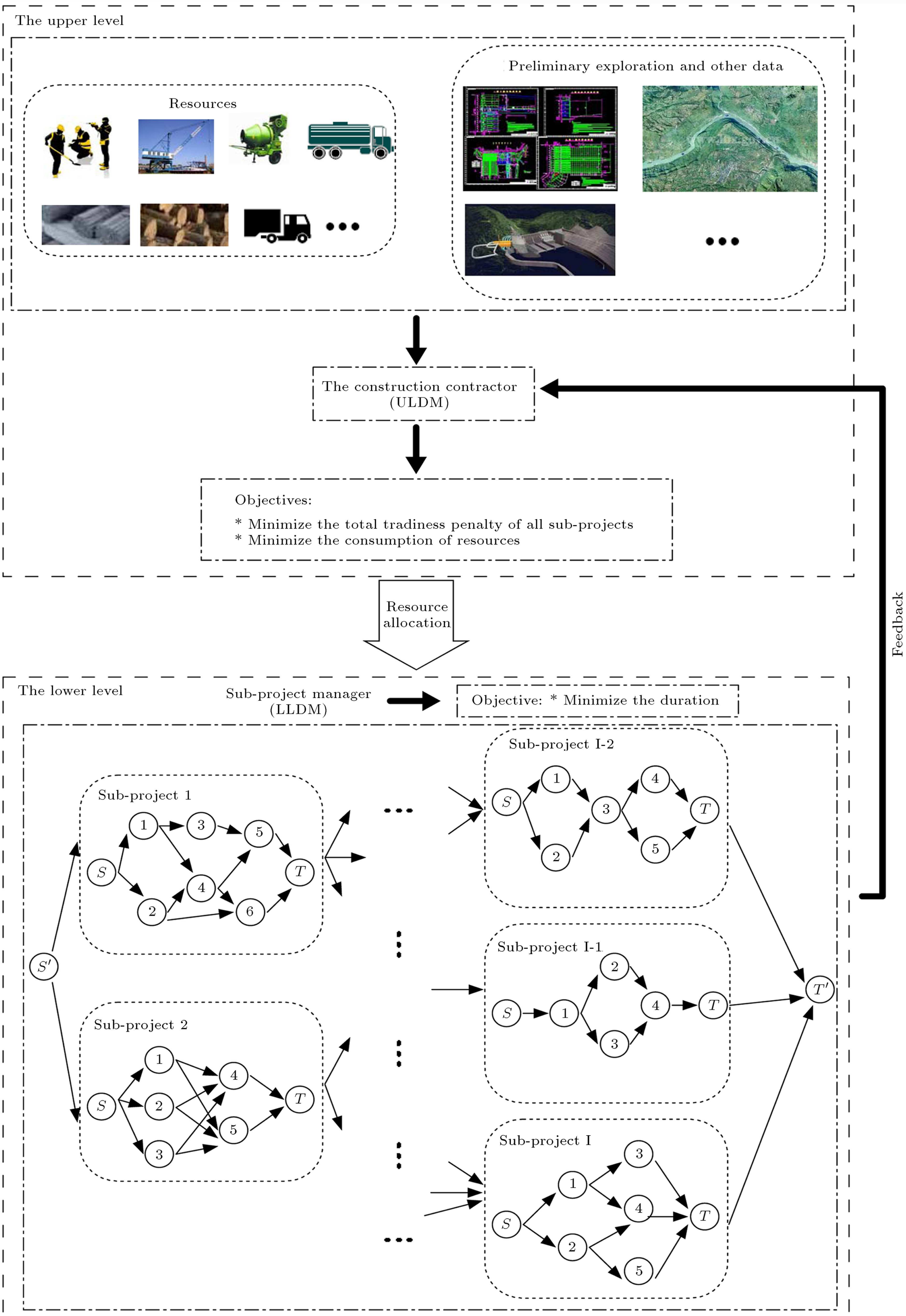

Figure 2. The decision structure of RCMPSP.

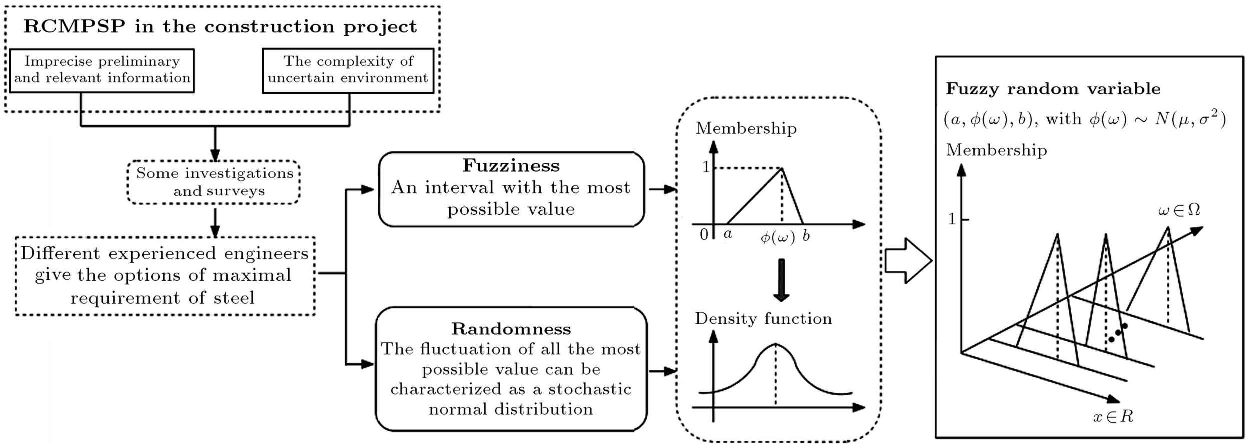

Figure 3. Flowchart of why the maximal requirement of steel is a fuzzy random variable.

the sub-project, and the processing time of activities in the sub-project are represented as triangular fuzzy random numbers. The details will be discussed further in the next section.

3. Fuzzy random bi-level RCMPSP modeling

Different from the classical resource constrained project scheduling problems, the RCMPSP can be stated as follows: A project consists of $I+2$ $(i = S', 1, 2, ..., I, T')$ sub-projects, where activities S' and T' are dummy (i.e., they do not have any duration, and just represent the initial and final sub-projects). There are $J + 2$ activities, A_{ij}, in the sub-projects, i, and activities S and T are also dummy. There exists a set of renewable resources, $k = \{1, 2, \cdots, K\}$ (such as equipment and labor), and non-renewable resources, $n = \{1, 2, \cdots, N\}$ (such as raw materials and cost consumption). A simple example of RCMPSP is shown in Figure 4.

To model this practical RCMPSP under a fuzzy random environment, the following descriptions are made:

1. The RCMPSP consists of I sub-projects which contain several activities.
2. The start time of each activity is dependent upon the completion of some other activities (precedence constraints of activities). After completing a specific activity, the next activity must also be started.
3. When a specific sub-project (precedence constraints of multiple projects) is initiated, it must be finished without changes to another sub-project.
4. Activities cannot be interrupted, and there is only one execution mode for each activity.
5. Multiple resources are available in limited quantities. The quantity of maximum renewable resources is $\hat{\tilde{r}}_k^M$ for resource k (where $\hat{\tilde{r}}_k^M$ is a fuzzy ran-

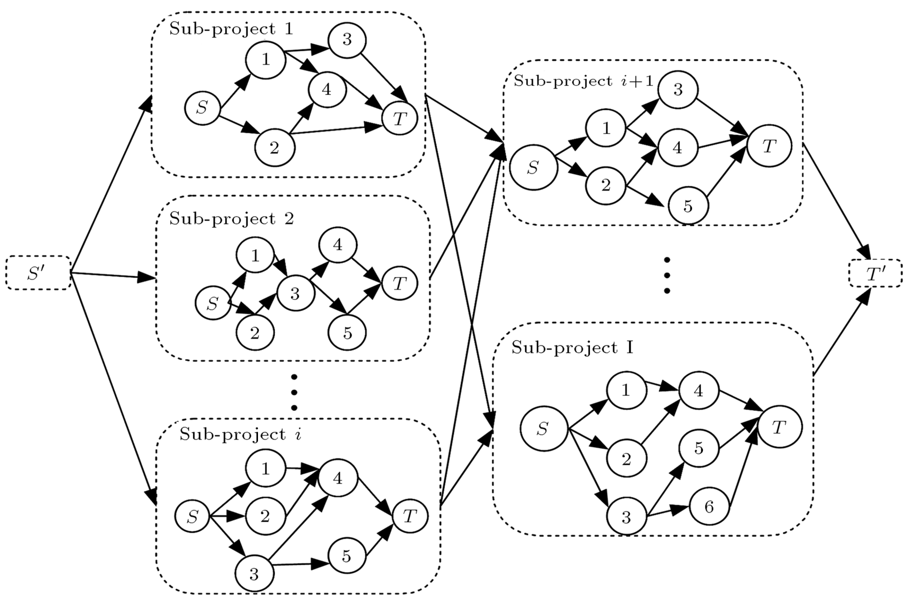

Figure 4. A simple example of RCMPSP [40].

dom variable), and the quantity of maximum no-renewable resources is r_n^M for resource n.

6. Each sub-project requires $s_r = \{1, 2, \cdots, S_r\}$ shared resources, including renewable and non-renewable resources. The requirement of activity A_{ij} during every stage is r_{ijs_r}, where the quantity of renewable resources is r_{ijk}, while non-renewable resources are r_{ijn} (i.e., $r_{ijs_r} = r_{ijk} + r_{ijn}$).
7. Except for the shared resources, the activities of each sub-project also require a separate resource. To simplify the problem, independent resource allocation is not considered in this paper, and all independent resources can meet the demand.
8. The duration of the activity, which requires the shared resources, is proportional to the workload in the sub-project, and inversely proportional to the allocation of shared resources.
9. The maximal quantity of renewable resources ($\hat{\tilde{r}}_k^M$), the penalty coefficient of each sub-project ($\hat{\tilde{c}}_i^{TP}$), the duration of sub-project ($\hat{\tilde{d}}_i$), and the processing time of activity j in the sub-project i ($\hat{\tilde{d}}_{ij}$) are fuzzy random variables.
10. The objectives of the upper level are to minimize the total tardiness penalty of all sub-projects and the consumption of resources, while the objective of the lower level is to minimize the duration of each sub-project.

3.1. Notation

In order to facilitate mathematical descriptions in the RCMPSP, the following notation is introduced:

i : Sub-project index;

j : Activity index in each sub-project;

k : Renewable resource index;

n : Non-renewable resource index;

t : Time index;

I_t : The set of activities being in progress in time t;

Pre(o) : The set of immediate predecessors of sub-project i;

Pre(j) : The set of immediate predecessors of activity j;

$\hat{\tilde{c}}_i^{TP}$: The penalty coefficient of sub-project i;

U_i : The workload of sub-project i, which uses the shared resources;

$\hat{\tilde{d}}_i$: The duration of sub-project i, which uses the shared resources;

$\hat{\tilde{d}}_{ij}$: The duration of activity j, which uses the shared resources in sub-project i;

d_i^D : The duration of sub-project i, which uses independent resources;

t_i^E : The due date of the sub-project, i;

t_i^f : The finish time of sub-project i;

t_{ij}^f : The finish time of activity j in sub-project i;

t_{ij}^{EF} : The earliest finish time of activity j in sub-project i;

t_{ij}^{LF} : The latest finish time of activity j in sub-project i;

r_{ijk} : The quantity of shared renewable resource, k, for activity j in sub-project i;

r_{ijn} : The quantity of shared non-renewable resource, n, for activity j in sub-project i;

$\hat{\tilde{r}}_k^M$: The maximal quantity of renewable resources;

r_n^M : The maximal quantity of non-renewable resources;

x_{ijt} : $x_{ijt} = \begin{cases} 1, & \text{if activity } j \text{ in sub-project } i \text{ is;} \\ & \text{scheduled to be finished in time } t \\ 0, & \text{otherwise} \end{cases}$

3.2. Fuzzy random bi-level RCMPSP model formulation

Based on the requirements of ULDM and LLDM, a fuzzy random bi-level RCMPSP model is proposed as follows.

Upper level model for the bi-level RCMPSP. For the RCMPSP in large-scale construction projects, the first objective of ULDM is to minimize the total tardiness penalty, which is the sum of penalty costs for all sub-projects, i.e.:

$$\min C = \sum_{i=1}^{I} \hat{\tilde{c}}_i^{TP} \left|(t_i^f - t_i^E)\right|. \tag{1}$$

Furthermore, the second objective of ULDM is to minimize the consumption of resources, i.e.:

$$\min R = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{s_r=1}^{S_r} r_{ijs_r}. \tag{2}$$

The constraints for the upper level in RCMPSP are divided into resource constraints and other logical constraints. Multiple resources are available in limited quantities, so, constraints:

$$\sum_{i=1}^{I} \sum_{j=1}^{J} r_{ijk} \sum_{\tau=t}^{t+d_{jm}-1} x_{ij\tau} \leq \hat{\tilde{r}}_k^M, \ \forall i, j, k$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} r_{ijn} \sum_{t=t_{ij}^{EF}}^{t_{ij}^{LF}} x_{ijt} \leq r_n^M, \ \forall j,k,n, \tag{3}$$

can be employed. In addition, in order to describe some non-negative variables for practical purposes, we can use:

$$t_i^f \geq 0; t_{ij}^{EF} \geq 0; t_{ij}^{EF} \geq 0; r_{ijk} \geq 0; r_{ijn} \geq 0$$

$$\forall\, i = 1,2,\cdots,I; j = 1,2,\cdots,J; k = 1,2,\cdots,K. \tag{4}$$

Thus, we have the upper level model as:

$$\begin{cases} \min C = \sum_{i=1}^{I} \hat{\tilde{c}}_i^{TP} \left|(t_i^f - t_i^E)\right| \\ \min R = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s_r=1}^{S_r} r_{ijs_r} \\ \text{s.t.} \begin{cases} \sum_{i=1}^{I}\sum_{j=1}^{J} r_{ijk} \sum_{\tau=t}^{t+d_{jm}-1} x_{ij\tau} \leq \hat{\tilde{r}}_k^M, \\ \quad \forall i,j,k \\ \sum_{i=1}^{I}\sum_{j=1}^{J} r_{ijn} \sum_{t=t_j^{EF}}^{t_j^{LF}} x_{ijt} \leq r_n^M, \\ \quad \forall j,k,n \\ t_i^f \geq 0, t_{ij}^{EF} \geq 0, t_{ij}^{EF} \geq 0 \\ r_{ijk} \geq 0, r_{ijn} \geq 0 \\ x_{ijt} = \{0,1\} \\ i = 1,2,\cdots,I; j = 1,2,\cdots,J; \\ \quad k = 1,2,\cdots,K \end{cases} \end{cases} \tag{5}$$

Lower level model for the bi-level RCMPSP. For the LLDM, the objective is to minimize the finish time of the sub-project. In this study, we use the sum of all the durations of the sub-projects:

$$\min T = \sum_{i=1}^{I}(t_i^f - t_o^f), \tag{6}$$

where $o \in \text{Pre}_i$. Let x_{ois_r} be a 0-1 variable, and:

$$x_{ois_r} = \begin{cases} 1, & \text{if } o,i \text{ consumes the shared resources } s_r \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

Thus, if sub-projects o, i ($o \in \text{Pre}_i$) consume the shared resources, s_r, then, the duration of i is $\sum_{s_r=1}^{S_r} \frac{U_i}{r_{is_r}}$. If they only consume independent resources, the duration is d_i^D.

$$x_{ois_r} \cdot \hat{\tilde{d}}_i = \begin{cases} \sum_{s_r=1}^{S_r} \frac{U_i}{r_{is_r}} \\ d_i^D \end{cases} \tag{8}$$

In addition, since the sub-project and the activity in the sub-project should meet precedence constraints, the relationship should be:

$$x_{ois_r} \cdot \hat{\tilde{d}}_i \leq x_{ois_r}(t_i^f - t_o^f), \quad x_{ois_r} \cdot \hat{\tilde{d}}_{ij} \leq x_{ois_r}(t_{ij}^f - t_{il}^f), \tag{9}$$

where $l \in \text{Pre}_j$. Finally, the logical constraints are also satisfied.

$$U_i \geq 0, t_i^f \geq 0, t_{ij}^f \geq 0. \tag{10}$$

Hence, we have the lower level model as:

$$\begin{cases} \min T = \sum_{i=1}^{I}(t_i^f - t_o^f) \\ \text{s.t.} \begin{cases} x_{ois_r} \cdot \hat{\tilde{d}}_i \leq x_{ois_r}(t_i^f - t_o^f) \\ x_{ois_r} \cdot \hat{\tilde{d}}_{ij} \leq x_{ois_r}(t_{ij}^f - t_{il}^f) \\ x_{ois_r} \cdot \hat{\tilde{d}}_i = \begin{cases} \sum_{s_r=1}^{S_r} \frac{U_i}{r_{is_r}} \\ d_i^D \end{cases} \\ x_{ois_r} = \{0,1\} \\ U_i \geq 0, t_i^f \geq 0, t_{ij}^f \geq 0 \\ o, i = 1,2,\cdots,I; j = 1,2,\cdots,J \\ o \in \text{Pre}_i; l \in \text{Pre}_j \end{cases} \end{cases} \tag{11}$$

Global model for the bi-level RCMPSP. Based on the discussion above, by integrating Eqs. (1) to (11), the following global model for the bi-level multi-objective RCMPSP model under a fuzzy random environment is formulated for the large-scale construction project:

$$\begin{cases} \min C = \sum_{i=1}^{I} \hat{\tilde{c}}_i^{TP} \left|(t_i^f - t_i^E)\right| \\ \min R = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s_r=1}^{S_r} r_{ijs_r} \\ \text{s.t.} \begin{cases} \sum_{i=1}^{I}\sum_{j=1}^{J} r_{ijk} \sum_{\tau=t}^{t+d_{jm}-1} x_{ij\tau} \leq \hat{\tilde{r}}_k^M, \ \forall i,j,k \\ \sum_{i=1}^{I}\sum_{j=1}^{J} r_{ijn} \sum_{t=t_j^{EF}}^{t_j^{LF}} x_{ijt} \leq r_n^M, \ \forall j,k,n \\ x_{ijt} = \begin{cases} 1, & \text{if activitiy } j \text{ in the sub-project } i \\ & \text{scheduled to be finished in time } t \\ 0, & \text{otherwise} \end{cases} \\ t_i^f \geq 0, t_{ij}^{EF} \geq 0, t_{ij}^{EF} \geq 0, r_{ijk} \geq 0, r_{ijn} \geq 0 \\ i = 1,2,\cdots,I; j = 1,2,\cdots,J; k = 1,2,\cdots,K \\ \quad \min T = \sum_{i=1}^{I}(t_i^f - t_o^f) \\ \quad \text{s.t.} \begin{cases} x_{ois_r} \cdot \hat{\tilde{d}}_i \leq x_{ois_r}(t_i^f - t_o^f) \\ x_{ois_r} \cdot \hat{\tilde{d}}_{ij} \leq x_{ois_r}(t_{ij}^f - t_{il}^f) \\ x_{ois_r} \cdot \hat{\tilde{d}}_i = \begin{cases} \sum_{s_r=1}^{S_r} \frac{U_i}{r_{is_r}} \\ d_i^D \end{cases} \\ x_{ois_r} = \begin{cases} 1, & \text{if } o,i \text{ consume the shared} \\ & \text{resources } s_r \\ 0, & \text{otherwise} \end{cases} \\ U_i, t_i^f, t_{ij}^f \geq 0 \\ o, i = 1,2,\cdots,I; j = 1,2,\cdots,J \\ o \in \text{Pre}_i; l \in \text{Pre}_j \end{cases} \end{cases} \end{cases}$$

3.3. Dealing with fuzzy random variables

Since some coefficients involved in the proposed bi-level RCMPSP model are triangular fuzzy random numbers, it is very hard to solve. In this case, considering the optimistic-pessimistic attitude of DMs, a hybrid crisp approach is employed to transfer the fuzzy random bi-level PCMPSP model to an equivalent one. This method transforms the fuzzy random parameter into a (α, β)-level trapezoidal fuzzy variable at first, and then defuzzifies the trapezoidal fuzzy variable by an expected value operator. Motivated by the form of the fuzzy random variable in the model, we consider the definition proposed by Puri and Ralescu [41], i.e. the fuzzy random variable is a measurable function from a probability space to a collection of fuzzy variables. Denoting the fuzzy random coefficient as $\hat{\tilde{\xi}} = (\xi_L, \phi(\omega), \ \varepsilon_R)$ (where $\phi(\omega)$ follows a normal distribution $N(\mu, \sigma^2)$), the given possibility level of fuzzy variable is α, and the given probability level of the random variable is β. These parameters, ξ_L, ξ_R, μ, and σ, are estimated by collected data and professional experience using statistical methods. After that, we can obtain the DMs's degree of optimism, α and β, through a group decision making approach.

Now, let the probability density function of $\phi(\omega)$ be $p_\phi(x)$. Then, the β-level set of $\phi(\omega)$ is $\phi_\beta = [\phi_\beta^L, \phi_\beta^R] = \{x \in U | p_\phi(x) \geq \beta\}$ (see Figure 5).

If $p_\phi(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} = \beta$, then, we get:

$$x = \mu \pm \sqrt{-2\sigma^2 \ln(\sqrt{2\pi}\beta\sigma)}.$$

It means that:

$$\phi_\beta^L = \mu - \sqrt{-2\sigma^2 \ln(\sqrt{2\pi}\beta\sigma)},$$

$$\phi_\beta^R = \mu + \sqrt{-2\sigma^2 \ln(\sqrt{2\pi}\beta\sigma)}. \quad (12)$$

Thus, $\hat{\tilde{\xi}} = (\xi_L, \phi(\omega), \xi_R)$ is transferred as a class of triangular fuzzy numbers (see Figure 6).

Subsequently, for the given possibility level, α, we can get the α-level set of these triangular fuzzy numbers as Figure 7.

From Figure 7, we can see that the fuzzy random variable, $\hat{\tilde{\xi}} = (\xi_L, \phi(\omega), \xi_R)$, is transferred as a trapezoidal fuzzy variable, $\hat{\tilde{\xi}} \to \tilde{\xi}_{(\alpha,\beta)} = (\xi_L, \underline{\xi}, \overline{\xi}, \xi_R)$ (the

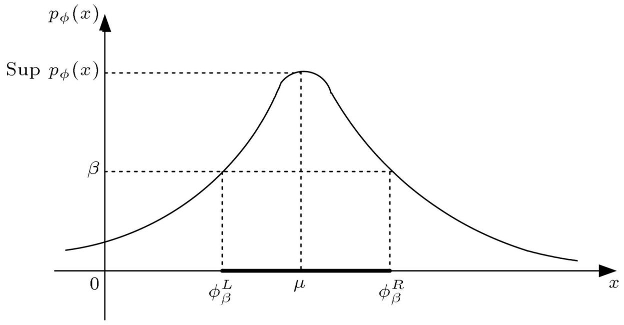

Figure 5. The probability density function $p_\phi(x)$.

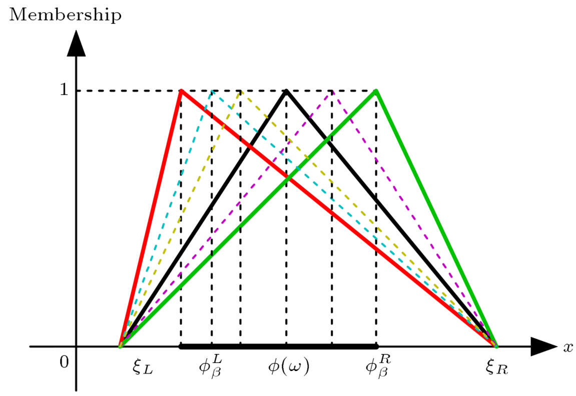

Figure 6. Transferring the fuzzy random variable to a class of triangular fuzzy number (Step 1).

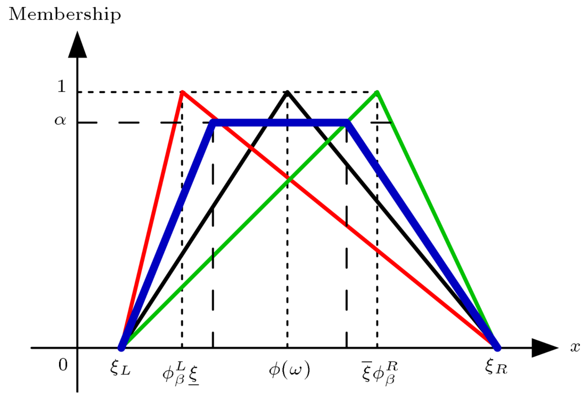

Figure 7. Transfering the fuzzy random variable to a trapezoidal fuzzy number (Step 2).

blue one), where:

$$\underline{\xi} = \xi_R - \alpha(\xi_R - \phi_\beta^L) \quad \text{and} \quad \overline{\xi} = \xi_L + \alpha(\phi_\beta^R - \xi_L). \quad (13)$$

Hence, the fuzzy random variables, $\hat{\tilde{c}}_i^{TP}$, $\hat{\tilde{r}}_k^M$, $\hat{\tilde{d}}_i$, and $\hat{\tilde{d}}_{ij}$, in the proposed model can be transformed into (α, β)-level trapezoidal fuzzy variables, as follows:

$$\hat{\tilde{c}}_i^{TP} \to \tilde{c}_{i_{(\alpha_1,\beta_1)}}^{TP} = ([c_i^{TP}]_L, \underline{c}_i^{TP}, \overline{c}_i^{TP}, [c_i^{TP}]_R),$$

$$\hat{\tilde{r}}_k^M \to \tilde{r}_{k_{(\alpha_2,\beta_2)}}^M = ([r_k^M]_L, \underline{r}_k^M, \overline{r}_k^M, [r_k^M]_R),$$

$$\hat{\tilde{d}}_i \to \tilde{d}_{i_{(\alpha_3,\beta_3)}} = ([d_i]_L, \underline{d}_i, \overline{d}_i, [d_i]_R),$$

$$\hat{\tilde{d}}_{ij} \to \tilde{d}_{ij_{(\alpha_4,\beta_4)}} = ([d_{ij}]_L, \underline{d}_{ij}, \overline{d}_{ij}, [d_{ij}]_R). \quad (14)$$

Finally, a new measure with an optimistic-pessimistic adjustment index, Me, which is proposed by Xu and Zhou [42] for dealing with the trapezoidal fuzzy variable, is employed. The measure, Me, can evaluate the confidence degree that a fuzzy variable takes in an interval, and the expected value of the trapezoidal fuzzy variable can be obtained by Me as:

$$E^{Me}[\tilde{\xi} = (\xi_L, \underline{\xi}, \overline{\xi}, \xi_R)] = \frac{1-\lambda}{2}(\xi_L + \underline{\xi}) + \frac{\lambda}{2}(\overline{\xi} + \xi_R), \quad (15)$$

where λ is the optimistic-pessimistic index of DMs, and $\lambda = 1$ indicates that the best case has the maximal chance of occurring, while $\lambda = 0$ is opposite. Therefore, we have:

$$E^{Me}[\tilde{c}^{TP}_{i_{(\alpha_1,\beta_1)}}] = \frac{1-\lambda_1}{2}([c_i^{TP}]_L + \underline{c}_i^{TP}) + \frac{\lambda_1}{2}(\overline{c}_i^{TP} + [c_i^{TP}]_R),$$

$$E^{Me}[\tilde{r}^{M}_{k_{(\alpha_2,\beta_2)}}] = \frac{1-\lambda_2}{2}([r_k^{M}]_L + \underline{r}_k^{M}) + \frac{\lambda_2}{2}(\overline{r}_k^{M} + [r_k^{M}]_R),$$

$$E^{Me}[\tilde{d}_{i_{(\alpha_3,\beta_3)}}] = \frac{1-\lambda_3}{2}([d_i]_L + \underline{d}_i) + \frac{\lambda_3}{2}(\overline{d}_i + [d_i]_R),$$

$$E^{Me}[\tilde{d}_{ij_{(\alpha_4,\beta_4)}}] = \frac{1-\lambda_4}{2}([d_{ij}]_L + \underline{d}_{ij}) + \frac{\lambda_4}{2}(\overline{d}_{ij} + [d_{ij}]_R), \tag{16}$$

where parameters $[\cdot]_L$, $[\cdot]_R$, μ, σ, α, β and λ have been gained previously by statistical methods, and $\underline{[\cdot]}$ and $\overline{[\cdot]}$ can be calculated by Eqs. (12) and (13).

Based on the above hybrid method, the fuzzy random bi-level RCMPSP model can be transformed into the following equivalent crisp model:

$$\begin{cases}
\min C = \sum_{i=1}^{I} E^{Me}\left[\tilde{c}^{TP}_{i_{(\alpha_1,\beta_1)}}\right]\left|(t_i^f - t_i^E)\right| \\
\min R = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s_r=1}^{S_r} r_{ijs_r} \\
\text{s.t.}\begin{cases}
\sum_{i=1}^{I}\sum_{j=1}^{J} r_{ijk}\sum_{\tau=t}^{t+d_{jm}-1} x_{ij\tau} \le E^{Me}\left[\tilde{r}^M_{k_{(\alpha_2,\beta_2)}}\right], \forall i,j,k \\
\sum_{i=1}^{I}\sum_{j=1}^{J} r_{ijn}\sum_{t=t_j^{EF}}^{t_j^{LF}} x_{ijt} \le r_n^M,\ \forall j,k,n \\
x_{ijt} = \begin{cases} 1, & \text{if activity } j \text{ in the sub-project } i \text{ scheduled to be finished in time } t \\ 0, & \text{otherwise} \end{cases} \\
t_i^f \ge 0, t_{ij}^{EF} \ge 0, t_{ij}^{EF} \ge 0, r_{ijk} \ge 0, r_{ijn} \ge 0 \\
i = 1,2,\cdots,I; j = 1,2,\cdots,J; k = 1,2,\cdots,K \\
\min T = \sum_{i=1}^{I}(t_i^f - t_o^f) \\
\text{s.t.}\begin{cases}
x_{ois_r}\cdot E^{Me}\left[\tilde{d}_{i_{(\alpha_3,\beta_3)}}\right] \le x_{ois_r}(t_i^f - t_o^f) \\
x_{ois_r}\cdot E^{Me}\left[\tilde{d}_{ij_{(\alpha_4,\beta_4)}}\right] \le x_{ois_r}(t_{ij}^f - t_{il}^f) \\
x_{ois_r}\cdot E^{Me}\left[\tilde{d}_{i_{(\alpha_3,\beta_3)}}\right] = \begin{cases} \sum_{s_r=1}^{S_r}\frac{U_i}{r_{is_r}} \\ d_i^D \end{cases} \\
x_{ois_r} = \begin{cases} 1, & \text{if } o,i \text{ consume the shared resources } s_r \\ 0, & \text{otherwise} \end{cases} \\
U_i, t_i^f, t_{ij}^f \ge 0 \\
o,i = 1,2,\cdots,I; j = 1,2,\cdots,J \\
o \in \mathrm{Pre}_i; l \in \mathrm{Pre}_j
\end{cases}
\end{cases}
\end{cases}$$

4. Multiple Objective Bi-Level Adaptive Particle Swarm Optimization algorithm (MOBL-APSO)

Due to the superior search performance and fast convergence, the Particle Swarm Optimization (PSO) algorithm (first proposed by Kennedy and Eberhart in 1995 [43]), is considered an effective tool for solving optimization problems. It simulates the social behaviors of birds flocking to a promising position for certain objectives in multi-dimensional space [44]. In PSO, an n-dimensional position of a particle represents a solution, and the particles fly through the problem space following the current optimum particles. The updating mechanism of the particle is:

$$v_d^i(\tau+1) = w(\tau)v_d^i(\tau) + c_p r_1[p_d^{i,best}(\tau) - p_d^i(\tau)] + c_g r_2[g_d^{i,best}(\tau) - p_d^i(\tau)]$$

$$p_d^i(\tau+1) = p_d^i(\tau) + v_d^i(\tau+1), \tag{17}$$

where $v_d^i(\tau)$ is the velocity of the ith particle at the dth dimension in the τth iteration, w is an inertia weight, $p_d^i(\tau)$ is the position of the ith particle, r_1 and r_2 are random numbers in the range $[0,1]$, c_p and c_g are personal and global best position acceleration constants and, $p_d^{i,\text{best}}$ and $g_d^{i,\text{best}}$ are the personal and global best positions of the ith particle at the dth dimension.

Since PSO can be implemented easily and effectively, the researchers also consider PSO to be a very strong competitor with other algorithms in solving multi-objective decision making problems [45]. Some studies reported in the literature have extended PSO to multi-objective problems, such as Zhang et al. [46], Tavakkoli-Moghaddam et al. [47], Damghani et al. [48], Garg and Sharma [49], and so on. The improved approach employs the concept of Pareto dominance to determine the flight direction, and it maintains previously found non-dominated vectors in a global repository [45]. All the particles of this swarm are compared to each other and the non-dominated particles are stored in the repository. Different from classical PSO, the positions of particles are updated by:

$$v_d^i(\tau+1) = wv_d^i(\tau) + c_p r_1[p_d^{i,best}(\tau) - p_d^i(\tau)] + c_g r_2[REP(\tau) - p_d^i(\tau)], \tag{18}$$

where REP is the positions of the particles that represent non-dominated vectors in the repository, i.e. several equally good non-dominated solutions stored in the external repository instead of the global best position, $g_d^{i,best}(\tau)$.

This paper will apply a Multiple Objective Bi-Level Adaptive Particle Swarm Optimization algorithm (MOBL-APSO) to solve the proposed mathematical model. As an NP-hard problem, bi-level programming is difficult to obtain an analytical optimal solution (Ben-Ayed and Blair [50], especially for a multi-objective one. In this condition, MOBL-APSO is designed using a combination of the Pareto Archived Evolution Strategy (PAES) [51] and passive congregation (PSO-PC [52]). The following notation is used to MOBL-APSO for RCMPSP:

u: Upper-level particle index, $u = 1, 2, \cdots, U$;
l: Lower-level particle index, $l = 1, 2, \cdots, L$;
τ_u: Iteration index of the upper level, $\tau_u = 1, 2, \cdots, T_u$;
τ_l: Iteration index of the lower level, $\tau_l = 1, 2, \cdots, T_l$;
d: Dimension index, $d = 1, 2, \cdots, D$;
r_1, r_2, r_3, r_4, r_5: Uniform distributed random number within $[0, 1]$;
$w_u(\tau_u)$, $w_l(\tau_l)$: Inertia weight of upper and lower level;
c_{p_u}, c_{p_l}: Personal best position acceleration constant of upper and lower level;
c_{g_u}, c_{g_l}: Global best position acceleration constant of upper and lower level;
c_{pc}: Passive congregation coefficient;
$P^u(\tau_u), P^l(\tau_l)$: Vector position, i.e. the uth candidate solution for ULDM and the lth candidate solution for LLDM;
$V^u(\tau_u), V^l(\tau_l)$: Vector velocity of the uth particle in the τ_u iteration and lth particle in the τ_l iteration;
$P^{u,best}(\tau_u), P^{l,best}(\tau_l)$: Vector personal best position;
$G^{l,best}(\tau_l)$: Global best position of the lth particle in the τ_l iteration;
$p^l_{pc}(\tau_l)$: Particle selected randomly from the swarm in the τ_l iteration;
REP: The positions of the particles that represent non-dominated vectors in the repository.

4.1. Multiple Objective Adaptive PSO (MO-APSO) for the upper level programming

For the upper level programming, the solution approach combines multi-objective PSO with the Pareto Archived Evolution Strategy (PAES), which is one of the Pareto-based approaches to update the best position [51]. This approach employs a truncated archive, which is used to separate the objective space into a number of hypercubes, to store the elite individuals. Based on the density, every hypercube has its own score. After selecting the best of the particles based on the roulette wheel selection of the best hypercubes the particle is selected uniformly. Details of the PAES procedure, test procedure and selection procedure are stated below:

PAES procedure

Generate initial random solution $P^u(\tau_u)$ and add it to the archive
Update $P^u(\tau_u)$ to generate $P^u(\tau_u+1)$
  if $P^u(\tau_u)$ dominates $P^u(\tau_u+1)$ discard $P^u(\tau_u+1)$
  else if $P^u(\tau_u+1)$ dominates $P^u(\tau_u)$
    replace $P^u(\tau_u)$ with $P^u(\tau_u+1)$ and add $P^u(\tau_u+1)$ to the archive
  else if $P^u(\tau_u+1)$ is dominated by any member in the archive discard $P^u(\tau_u+1)$
  else if $P^u(\tau_u+1)$ dominates any member in the archive
    replace it with $P^u(\tau_u+1)$
  else if apply test procedure to $P^u(\tau_u)$, $P^u(\tau_u+1)$ and archive to determine which is the new current solution and whether add $P^u(\tau_u+1)$ to the archive or not
until a termination criterion is reached, otherwise return to line 2

Test procedure

if the archive is not full
  add $P^u(\tau_u+1)$ to the archive
  if $P^u(\tau_u+1)$ is in a less crowded region than $P^u(\tau_u)$ in the archive accept $P^u(\tau_u+1)$ as the new current solution
  else
    maintain $P^u(\tau_u)$ as the current solution
else
  if $P^u(\tau_u+1)$ is in a less crowded region than any other member add $P^u(\tau_u+1)$ to the archive, and remove a member of the archive from the most crowded region
    if $P^u(\tau_u+1)$ is in a less crowed region than $P^{u,best}(\tau_u)$
      accept $P^u(\tau_u+1)$ as the new current solution
    else
      maintain $P^u(\tau_u)$ as the current solution
else
  do not add $P^u(\tau_u+1)$ to the archive

Selection procedure

Step 1. Divide 1 by the number of particles in each hypercube to get its score.
Step 2. Select a hypercube by the roulette wheel selection according to the scores.
Step 3. Choose a particle in the selected hypercube uniformly.

Based on the above, the velocity and position of the particles are:

$$v^u_d(\tau_u+1) = w_u(\tau_u)v^u_d(\tau_u) + c_{p_u}r_1[p^{u,best}_d(\tau_u) - p^u_d(\tau_u)] + c_{g_u}r_2[REP(\tau_u) - p^u_d(\tau_u)]$$

$$p^u_d(\tau_u+1) = p^u_d(\tau_u) + v^u_d(\tau_u+1) \tag{19}$$

where $w_u = w(T_u) + \frac{\tau_u - T_u}{1-T_u}[w(1) - w(T_u)]$ [53].

4.2. PSO-PC for the lower level programming

Since there are many constraints in the lower level programming of the proposed model, we apply the PSO with Passive Congregation (PSO-PC) to avoid premature convergence. By adding the passive congregation coefficient into the standard PSO, PSO-PC will help the algorithm jump out of local optimal solution in the running process, and then improve the global search ability [52].

Let c_{pc} be the passive congregation coefficient, $p^l_{pc}(\tau_l)$ be a particle selected randomly from the swarm, and r_3, r_4, r_5 be the uniform distributed random numbers. Thus, the velocity and position are updated by:

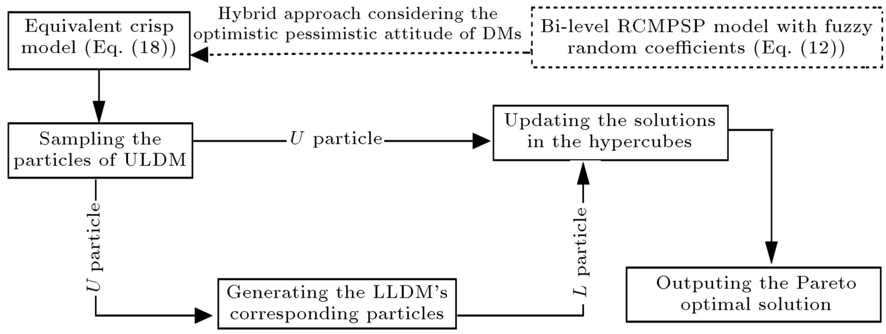

Figure 8. The outline of MOBL-APSO for the bi-level RCMPSP.

$$v_d^l(\tau_l+1)=w_l(\tau_l)v_d^l(\tau_l)+c_{p_l}r_3[p_d^{l,best}(\tau_l)-p_d^l(\tau_l)]$$
$$+c_{g_l}r_4[g_d^{l,best}(\tau_l)-p_d^l(\tau_l)]+c_{pc}r_5[p_{pc}^l(\tau_l)-p_d^l(\tau_l)],$$
$$p_d^l(\tau_l+1)=p_d^l(\tau_l)+v_d^l(\tau_l+1). \tag{20}$$

4.3. Overall procedure of MOBL-APSO

Based on the description above, the overall procedure of the MOBL-APSO algorithm for bi-level RCMPSP is:

MOBL-APSO algorithm for bi-level RCMPSP

Step 1. Initialize the velocity and position for the upper level particles. For $u=1,2,\cdots,U$, initialize the parameters: swarm size, iteration max, the range of position, inertia weight min, inertia weight max, c_{p_u}, c_{g_u};
Step 2. Check the feasibility of the upper level solutions: if the feasibility criterion is met by all particles, then continue. Otherwise, return to Step 1;
Step 3. By the initialization result of upper-level particles, apply PSO-PC to achieve the optimal objective for the lower-level programming;
Step 4. Calculate each fitness value using multi-objective methods in MO-APSO and restore the Pareto optimal solutions (i.e., the elite individuals) in REP;
Step 5. While the maximum number of cycles has not been reached
Do
Step 5.1: Update the velocity and the position of each particle by Eq. (19);
Step 5.2: Evaluate every particle and update the contents of REP and the geographical representation of the particles within the hypercubes. Insert all the currently non-dominated locations into the repository and eliminate any dominated locations from the repository;
Step 5.3: Use PAES, test procedure, and selection procedure to update the best position. Otherwise, the position in memory replaces the current one; if any of them is dominated by the other, select one of them randomly;
Step 5.4: Increment the loop counter.
Step 6. End while;
Step 7. If the stopping criterion is met, i.e., $\tau_u=T_u$, continue to Step 8. Otherwise, $\tau_u=\tau_u+1$ and return to Step 3;
Step 8. Decode REP as the optimal solution set.

The MOBL-APSO algorithm for the bi-level RCMPSP is outlined in Figure 8, and the overall procedure is presented in Figure 9.

5. Practical application

The bi-level RCMPSP considered in this paper is from the Phase II Project of the Xiangjiaba Hydropower Station. The following are representations of the case problem, data collection, case problem results and analysis.

5.1. Representation of the case problem

The Phase II Project in the Xiangjiaba Hydropower Station contains preparation, the aggregate processing system of the Mayanpo and Taiping raw material yard, river diversion, dam construction, spillway project, and power capacity of the stream. the Phase II Project uses months as the measure of duration, i.e., one month per unit. The duration, precedence relationship, and resource requirements of activities in each sub-project are shown in Figure 10. There are three types of resource in the Phase II Project, i.e. manpower (r_1, renewable resources), equipment (r_2, renewable resources) and material (r_3, nonrenewable resources). Manpower is composed of the vice-header, plasterer, installer, decorator, surveyor, electrician, ordinary worker, and so on. Equipment consists of a high portal crane, tower belt, concrete mixing plant, 480-ton gantry crane, translation cable machine, electric impact drill, and so on. Material involves cement, admixture, concrete, reinforcement, steel pipes, concrete accelerator, stabilizer, and so on. For calculating different resources expediently, the quantities of all resource consumption are transferred into a cash value (ten millions CNY per unit).

Manpower r_1 = actual number of workers × working time × wage;
Equipment r_2 = actual number of equipment × working time ×[cost of equipment purchases (or rental cost) + loss of equipment];
Material r_3 = actual demand × material price

5.2. Data collection

All detailed data of the Phase II Project in the Xiangjiaba Hydropower Station are gained from the Hy-

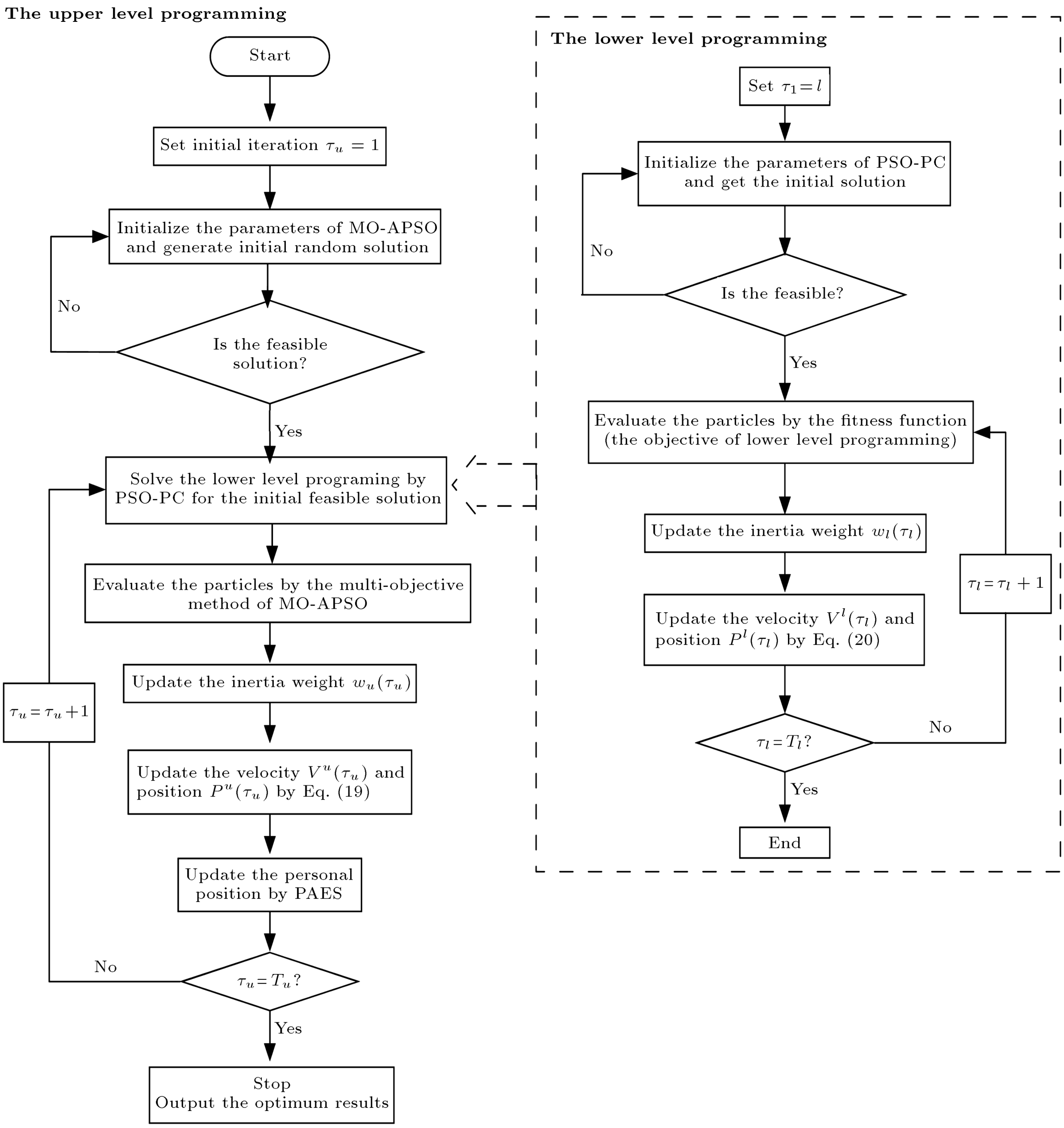

Figure 9. Framework of MOBL-APSO.

drochina Zhongnan Engineering Corporation (HZEC). The fuzzy random data, including the maximal quantity of renewable resources ($\hat{\tilde{r}}_k^M$), the penalty coefficient of each sub-project ($\hat{\tilde{c}}_i^{TP}$), the duration of the sub-project ($\hat{\tilde{d}}_i$), and the processing time of activity j in the sub-project i ($\hat{\tilde{d}}_{ij}$), are obtained based on previous data and experts' experience. The detailed information is shown in Table 1.

5.3. Results and analysis

The optimal scheduling scheme (the finish time of each sub-project and activity) and resource allocation is generated by MOBL-APSO. The parameters of MOBL-APSO for this practical case problem are: swarm size popsize, $L = 50$, iteration max, $T = 100$, personal and global best position acceleration constant of upper and lower levels, $c_{p_u} = c_{p_l} = c_{g_u} = c_{g_l} = 2$, passive congregation coefficient, $c_{pc} = 1$, and inertia weight of upper and lower levels, $w_u(1) = w_l(1) = 0.4, w_u(\tau_u) = w_l(\tau_l) = 0.9$. Using Mat lab 7.0 and Visual C++ language on a Inter Core I7 M370, 2.40 GHz, with 2048 MB memory, and taking the data above into the computer program, the case problem is solved by MOBL-APSO within 21 minutes, on average, which is accepted by the ULDM and LLDM. The dots in Figure 11 are the Pareto optimal solutions of upper level programming.

Following Figure 11, ULDM can choose the

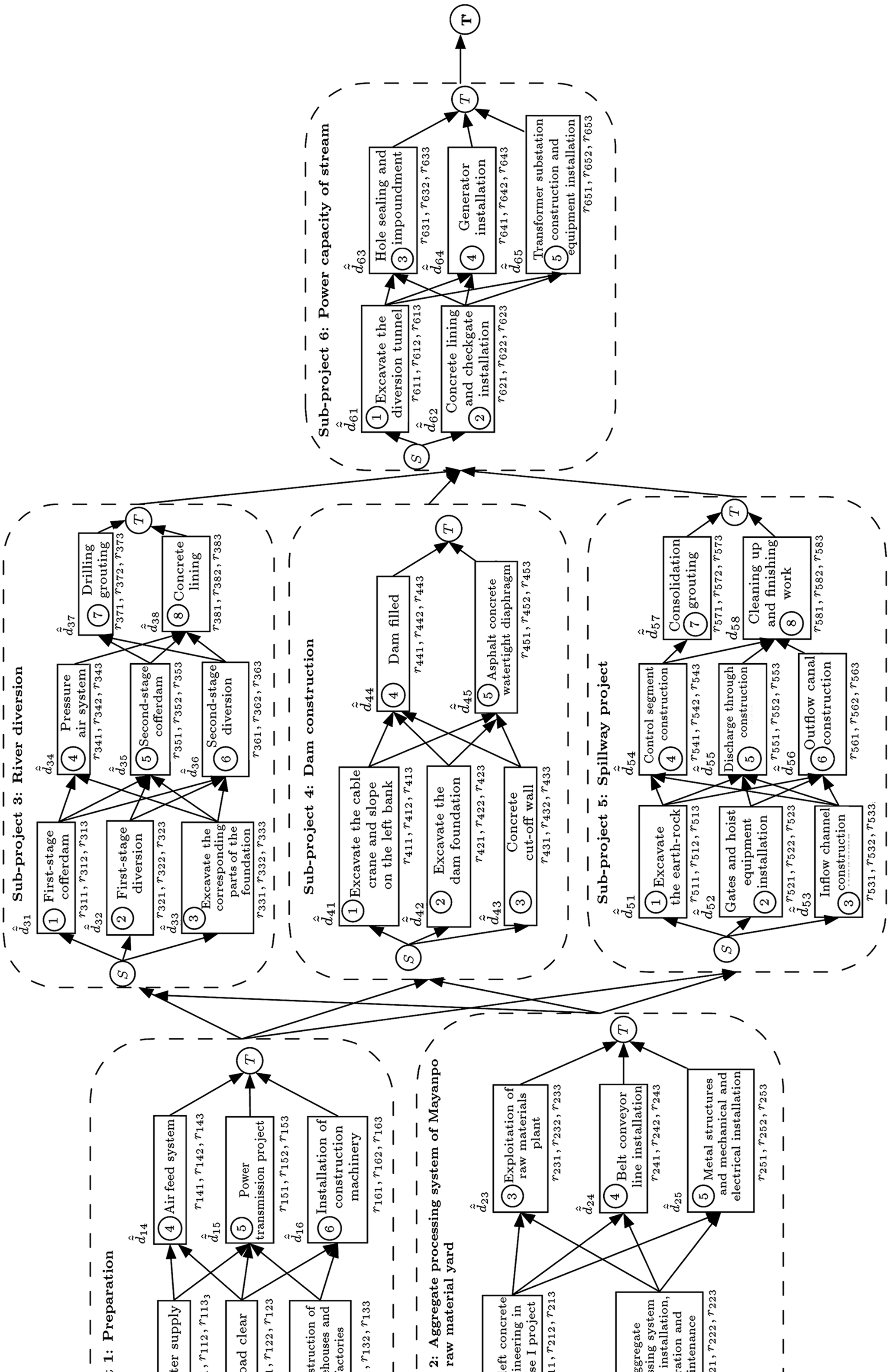

Figure 10. Configuration of RCMPSP in the Phase II Project.

Table 1. The data information.

Maximal quantity of resources	$\hat{\hat{r}}_1^M = (11.36, \phi(\omega_{r_1^M}), 14.25)$, $\phi(\omega_{r_1^M}) \sim N(12.00, 1.00)$; $\hat{\hat{r}}_2^M = (5.16, \phi(\omega_{r_2^M}), 8.00)$, $\phi(\omega_{r_2^M}) \sim N(5.75, 0.81)$ $r_3^M = 28$
Penalty coefficient of each sub-project	$\hat{\hat{c}}_1^{TP} = (1.26, \phi(\omega_{c_1^{TP}}), 1.58)$, $\phi(\omega_{c_1^{TP}}) \sim N(1.50, 4.00)$; $\hat{\hat{c}}_2^{TP} = (1.03, \phi(\omega_{c_2^{TP}}), 1.47)$, $\phi(\omega_{c_2^{TP}}) \sim N(1.25, 0.09)$ $\hat{\hat{c}}_3^{TP} = (1.76, \phi(\omega_{c_3^{TP}}), 2.04)$, $\phi(\omega_{c_3^{TP}}) \sim N(1.98, 1.00)$; $\hat{\hat{c}}_4^{TP} = (4.39, \phi(\omega_{c_4^{TP}}), 5.01)$, $\phi(\omega_{c_4^{TP}}) \sim N(4.86, 0.64)$ $\hat{\hat{c}}_5^{TP} = (2.61, \phi(\omega_{c_5^{TP}}), 2.98)$, $\phi(\omega_{c_5^{TP}}) \sim N(2.94, 0.49)$; $\hat{\hat{c}}_6^{TP} = (2.99, \phi(\omega_{c_6^{TP}}), 3.28)$, $\phi(\omega_{c_6^{TP}}) \sim N(3.14, 4.00)$
Duration of sub-project	$\hat{\hat{d}}_1 = (15.00, \phi(\omega_{d_1}), 17.33)$, $\phi(\omega_{d_1}) \sim N(15.84, 0.09)$; $\hat{\hat{d}}_2 = (12.69, \phi(\omega_{d_2}), 14.57)$, $\phi(\omega_{d_2}) \sim N(13.13, 1.00)$ $\hat{\hat{d}}_3 = (20.46, \phi(\omega_{d_3}), 22.41)$, $\phi(\omega_{d_3}) \sim N(21.85, 0.04)$; $\hat{\hat{d}}_4 = (48.67, \phi(\omega_{d_4}), 52.38)$, $\phi(\omega_{d_4}) \sim N(51.28, 0.64)$ $\hat{\hat{d}}_5 = (28.19, \phi(\omega_{d_5}), 32.49)$, $\phi(\omega_{d_5}) \sim N(31.51, 4.00)$; $\hat{\hat{d}}_6 = (30.66, \phi(\omega_{d_6}), 34.13)$, $\phi(\omega_{d_6}) \sim N(33.62, 0.81)$
Processing time of activity	$\hat{\hat{d}}_{11} = (7.08, \phi(\omega_{d_{11}}), 9.35)$, $\phi(\omega_{d_{11}}) \sim N(8.61, 1.00)$; $\hat{\hat{d}}_{12} = (4.38, \phi(\omega_{d_{12}}), 5.43)$, $\phi(\omega_{d_{12}}) \sim N(5.31, 0.09)$ $\hat{\hat{d}}_{13} = (5.13, \phi(\omega_{d_{13}}), 6.81)$, $\phi(\omega_{d_{13}}) \sim N(6.25, 0.49)$; $\hat{\hat{d}}_{14} = (3.58, \phi(\omega_{d_{14}}), 5.02)$, $\phi(\omega_{d_{14}}) \sim N(4.26, 4.00)$ $\hat{\hat{d}}_{15} = (3.96, \phi(\omega_{d_{15}}), 4.82)$, $\phi(\omega_{d_{15}}) \sim N(4.09, 1.00)$; $\hat{\hat{d}}_{16} = (6.39, \phi(\omega_{d_{16}}), 7.96)$, $\phi(\omega_{d_{16}}) \sim N(6.98, 9.00)$ $\hat{\hat{d}}_{21} = (2.84, \phi(\omega_{d_{21}}), 3.62)$, $\phi(\omega_{d_{21}}) \sim N(3.08, 0.04)$; $\hat{\hat{d}}_{22} = (4.68, \phi(\omega_{d_{22}}), 5.99)$, $\phi(\omega_{d_{22}}) \sim N(5.63, 1.00)$ $\hat{\hat{d}}_{23} = (3.52, \phi(\omega_{d_{23}}), 5.09)$, $\phi(\omega_{d_{23}}) \sim N(4.35, 0.64)$; $\hat{\hat{d}}_{24} = (3.95, \phi(\omega_{d_{24}}), 4.69)$, $\phi(\omega_{d_{24}}) \sim N(4.22, 0.09)$ $\hat{\hat{d}}_{25} = (6.58, \phi(\omega_{d_{25}}), 8.96)$, $\phi(\omega_{d_{25}}) \sim N(7.24, 1.00)$; $\hat{\hat{d}}_{31} = (5.68, \phi(\omega_{d_{31}}), 7.32)$, $\phi(\omega_{d_{31}}) \sim N(8.61, 4.00)$ $\hat{\hat{d}}_{32} = (6.14, \phi(\omega_{d_{32}}), 8.33)$, $\phi(\omega_{d_{32}}) \sim N(7.35, 0.01)$; $\hat{\hat{d}}_{33} = (3.33, \phi(\omega_{d_{33}}), 4.82)$, $\phi(\omega_{d_{33}}) \sim N(4.13, 1.00)$ $\hat{\hat{d}}_{34} = (5.79, \phi(\omega_{d_{34}}), 6.44)$, $\phi(\omega_{d_{34}}) \sim N(6.05, 0.01)$; $\hat{\hat{d}}_{35} = (4.58, \phi(\omega_{d_{35}}), 5.83)$, $\phi(\omega_{d_{35}}) \sim N(5.22, 0.09)$ $\hat{\hat{d}}_{36} = (3.92, \phi(\omega_{d_{36}}), 4.61)$, $\phi(\omega_{d_{36}}) \sim N(4.17, 0.81)$; $\hat{\hat{d}}_{37} = (5.21, \phi(\omega_{d_{37}}), 6.63)$, $\phi(\omega_{d_{37}}) \sim N(6.07, 0.09)$ $\hat{\hat{d}}_{38} = (3.43, \phi(\omega_{d_{38}}), 4.58)$, $\phi(\omega_{d_{38}}) \sim N(4.19, 1.00)$; $\hat{\hat{d}}_{41} = (11.23, \phi(\omega_{d_{41}}), 13.95)$, $\phi(\omega_{d_{41}}) \sim N(12.25, 1.00)$ $\hat{\hat{d}}_{42} = (17.24, \phi(\omega_{d_{42}}), 18.39)$, $\phi(\omega_{d_{42}}) \sim N(18.03, 0.49)$; $\hat{\hat{d}}_{43} = (19.76, \phi(\omega_{d_{43}}), 22.94)$, $\phi(\omega_{d_{43}}) \sim N(20.44, 0.01)$ $\hat{\hat{d}}_{44} = (23.68, \phi(\omega_{d_{44}}), 24.79)$, $\phi(\omega_{d_{44}}) \sim N(24.01, 1.00)$; $\hat{\hat{d}}_{45} = (15.13, \phi(\omega_{d_{45}}), 17.08)$, $\phi(\omega_{d_{45}}) \sim N(16.31, 0.64)$ $\hat{\hat{d}}_{51} = (9.89, \phi(\omega_{d_{51}}), 11.62)$, $\phi(\omega_{d_{51}}) \sim N(11.05, 0.04)$; $\hat{\hat{d}}_{52} = (4.48, \phi(\omega_{d_{52}}), 5.69)$, $\phi(\omega_{d_{52}}) \sim N(5.31, 1.00)$ $\hat{\hat{d}}_{53} = (11.25, \phi(\omega_{d_{53}}), 13.44)$, $\phi(\omega_{d_{53}}) \sim N(12.02, 1.00)$; $\hat{\hat{d}}_{54} = (10.36, \phi(\omega_{d_{54}}), 11.85)$, $\phi(\omega_{d_{54}}) \sim N(11.13, 4.00)$ $\hat{\hat{d}}_{55} = (7.95, \phi(\omega_{d_{55}}), 9.66)$, $\phi(\omega_{d_{55}}) \sim N(9.13, 0.16)$; $\hat{\hat{d}}_{56} = (9.22, \phi(\omega_{d_{56}}), 10.23)$, $\phi(\omega_{d_{56}}) \sim N(10.04, 1.00)$ $\hat{\hat{d}}_{57} = (8.09, \phi(\omega_{d_{57}}), 9.97)$, $\phi(\omega_{d_{57}}) \sim N(9.24, 0.25)$; $\hat{\hat{d}}_{58} = (4.94, \phi(\omega_{d_{58}}), 6.86)$, $\phi(\omega_{d_{58}}) \sim N(6.06, 0.49)$ $\hat{\hat{d}}_{61} = (7.79, \phi(\omega_{d_{61}}), 8.96)$, $\phi(\omega_{d_{61}}) \sim N(8.34, 1.00)$; $\hat{\hat{d}}_{62} = (9.26, \phi(\omega_{d_{62}}), 11.53)$, $\phi(\omega_{d_{62}}) \sim N(10.29, 0.25)$ $\hat{\hat{d}}_{63} = (21.44, \phi(\omega_{d_{63}}), 24.62)$, $\phi(\omega_{d_{63}}) \sim N(23.29, 1.00)$; $\hat{\hat{d}}_{64} = (15.09, \phi(\omega_{d_{64}}), 17.16)$, $\phi(\omega_{d_{64}}) \sim N(16.20, 0.36)$ $\hat{\hat{d}}_{65} = (13.36, \phi(\omega_{d_{65}}), 15.03)$, $\phi(\omega_{d_{65}}) \sim N(14.25, 1.00)$
Other parameters	$t_1^E = 20, t_2^E = 14, t_3^E = 39, t_4^E = 68, t_5^E = 51, t_6^E = 100$ $\alpha_1 = 0.5, \alpha_2 = 0.4, \alpha_3 = 0.8, \alpha_4 = 0.4$ $\beta_1 = 0.8, \beta_2 = 0.8, \beta_3 = 0.9, \beta_4 = 0.8$ $\lambda_1 = 0.75, \lambda_2 = 0.80, \lambda_3 = 0.64, \lambda_4 = 0.50$

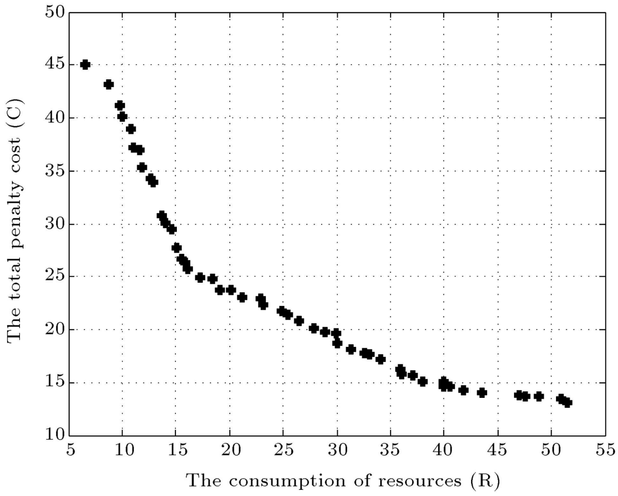

Figure 11. Pareto optimal solutions of upper level programming.

scheduling plan from these Pareto-optimal solutions, according to the actual situation of the Phase II Project in Xiangjiaba Hydropower Station. For example, if ULDM determines that the objective of the tardiness penalty is the more important factor, they may allow an increased resource consumptions. Thus, they would choose the far left Pareto-optimal solutions, such as $R = 40.9459$, $C = 15.9185$. In this situation, the minimal project duration is $T = 99.05$ months, and the following resource consumptions are: Manpower $r_1 = 10.6780$, Equipment $r_2 = 4.9234$, and Material $r_3 = 25.3445$, respectively. In addition, the project scheduling scheme is presented in Figure 12, and the finish time of each sub-project is shown in Figures 13-18. In practice, the DMs can change the relevant parameters to obtain different solutions under different levels of the parameters. The solutions reflect different optimistic-pessimistic attitudes for uncertainty and different predictions of probability and possibility levels.

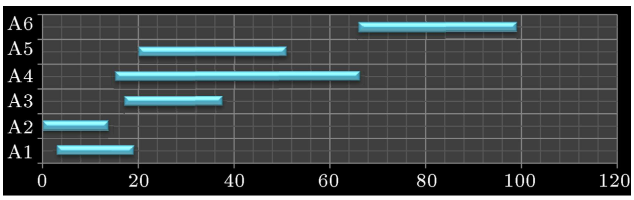

Figure 12. The overall scheduling scheme.

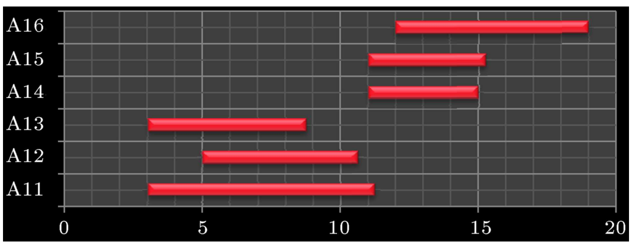

Figure 13. The schedule of sub-project-1.

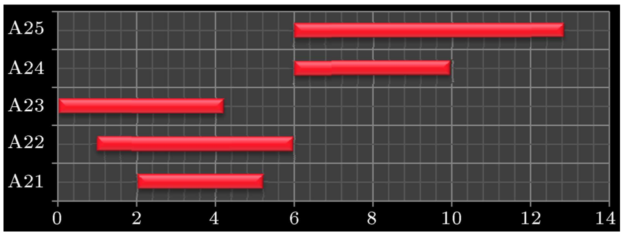

Figure 14. The schedule of sub-project-2.

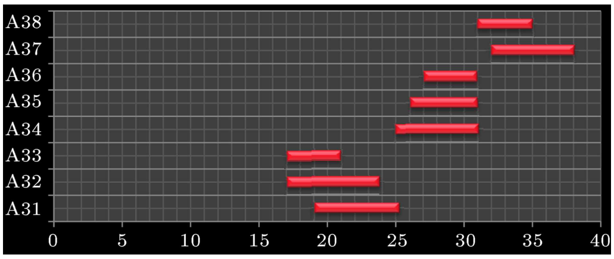

Figure 15. The schedule of sub-project-3.

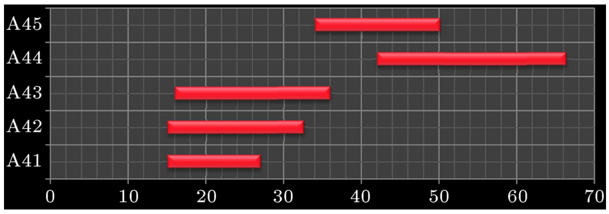

Figure 16. The schedule of sub-project-4.

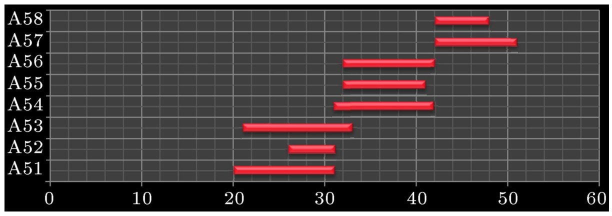

Figure 17. The schedule of sub-project-5.

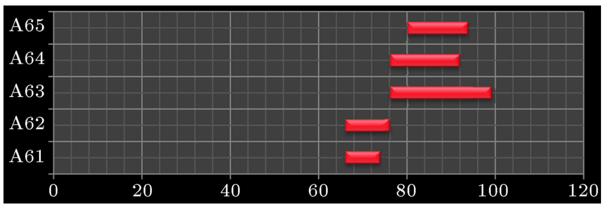

Figure 18. The schedule of sub-project-6.

6. Conclusions and further research

Considering the complex hierarchical organizational structure and the hybrid uncertain environment, where fuzziness and randomness co-exist, a bi-level multi-objective RCMPSP model with fuzzy random coefficients for the practical resource-constrained multiple project scheduling problems (RCMPSP) is presented in this paper. The fuzzy random coefficients are transformed into trapezoidal fuzzy variables by the

DMs's degree of optimism, α and β, which are finally de-fuzzified by the expected value index, λ. In order to solve the equivalent crisp model, the MOBL-APSO algorithm is designed to obtain the optimal solution. For illustrating the effectiveness, the proposed model and algorithm are applied to the Phase II Project in the Xiangjiaba Hydropower Station.

The main contributions of this study are as follows: (1) This study focuses on the RCMPSP with complex hierarchical organizational structure and a hybrid uncertain environment in the large-scale water conservancy and hydropower construction project, which has great practical significance. (2) The fuzzy random variable is employed in the practical bi-level multi-objective RCMPSP model to characterize the hybrid uncertain environment, and this work is original. (3) The proposed model is transferred to an equivalent crisp one by the DMs's degree of optimism α, β, and the expected value index λ. For solving the complex model, a Multi-Objective Bi-Level Adaptive Particle Swarm Optimization algorithm (MOBL-APSO) is designed as the solution method. (4) The model and algorithm are successfully applied to the practical case.

Future research has three aspects: Firstly, more realistic factors and constraints for the RCMPSP with complex hierarchical organizational structure should be considered. Secondly, more efficient heuristic methods should be designed to solve this NP-hard problems. Thirdly, software development based on the proposed mathematical model and MOBL-APSO algorithm in this paper is necessary. All are very important and worth equal concern.

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