IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received June 17, 2019, accepted June 24, 2019, date of publication July 3, 2019, date of current version July 22, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2926337

Proactive and Reactive Multi-Project Scheduling in Uncertain Environment

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This work was supported in part by the Youth Foundation of Ministry of Education of China under Grant 15XJC630007 and Grant 19YJC630141, in part by the Chongqing Education Committee Science and Technology Research Project under Grant KJ1500702, in part by the Chongqing Social Science Planning Project under Grant 2016BS080 and Grant 2018BS84, in part by the Chongqing Education Science Planning Project under Grant 2017-GX-317, in part by the Scientific and Technological Research Program of Chongqing Municipal Education Commission under Grant KJQN201800832, and in part by the Postdoctoral Fund Project of China under Grant 2017M612951 and Grant 2019M653385.

ABSTRACT In this paper, a proactive and reactive multi-project scheduling problem is addressed. This problem is related to the influences of uncertain factors, which leads to a deviation between actual scheduling and baseline scheduling, and a recovery strategy is established in order to generate a baseline scheduling scheme. This paper introduces a proactive multi-project scheduling sub-model. When the activity is interrupted, the proactive scheduling scheme is used as the baseline scheduling scheme, which is embedded in the reactive scheduling, and then, the reactive scheduling sub-model is established. The proposed model can be used to generate alternative schedules, and to meet this need, a genetic simulated annealing algorithm is proposed. A buffer change operator (SC) and a crossover operator are designed in a genetic simulated annealing algorithm so that in the early stages of the algorithm, an optimum individual is produced and protected. The performance comparison shows that the genetic simulated annealing algorithm significantly outperforms the previous algorithms.

INDEX TERMS Multi-project scheduling, proactive and reactive scheduling, genetic simulated annealing algorithm, optimization model.

I. INTRODUCTION

During the execution of a project, the baseline scheduling plan is often affected by uncertain factors, which cause the start time of activities to be postponed and the supply of resources to be interrupted. For example, the duration of an activity is modified temporarily, a new activity is introduced during the project execution, and the original activity is cancelled, all of which affected the total duration of the project. The baseline scheduling plan is adjusted, which is caused by uncertain factors during the project execution. Therefore, the scheduling process of the whole project became difficult to control.

The deterministic resource-constrained multi-project scheduling problems have been studied [1]–[3]. Each activity in the scheduling scheme has a definite beginning and ending time. When an emergent event occurs, the scheduling scheme deviates from the actual scheduling scheme, which may bring risks to the completion of the project. Interference incidents is refer to some uncertain factors in the scheduling execution, such as equipment failure, bad weather, resource change and so on. The uncertain factors in multi-project scheduling are mainly divided into two categories. The first kind is the uncertainty caused by the external environment. The number of activities are increased because of the customers increased the orders temporarily, the duration is delayed due to the uncertainty information or activities cannot be executed normally because of the factors such as climate or weather [4]. The second kind is the uncertainty of the production factors, which can also be called the uncertainty of the resources. The most common uncertainties of production factors are the temporary shortage of resources and equipment failure. In multi-project scheduling, the influence of uncertainty factors on the scheduling scheme are

The associate editor coordinating the review of this manuscript and approving it for publication was Sotirios Goudos.

more complex. The influence of uncertain factors on the scheduling system may occur at any time in the execution process [5]. Therefore, the completion time of each activity cannot be accurately grasped, when making a multi-project scheduling plan, which weakens the performance of multi-project reference scheduling. According to the impact of uncertain factors on multi-project scheduling, frequent changes to scheduling plans affect the robustness of scheduling seriously and greatly increases the risk of the delayed duration.

The research on proactive and reactive scheduling methods in the existing literature indicate that scheduling stability is enhanced by a setting time buffer or resource buffer, because of the constraints concerning resource availability and the time window during the scheduling process. Irrespective of how robust, proactive and reactive the scheduling is, it is impossible to determine the influence on project scheduling with certainty. Ma *et al.* [6] and Deblaere *et al.* [7] proposed that reactive scheduling involves optimizing the scheduling process, random interferences were found, and a response scheduling plan was proposed, which affect the normal baseline scheduling with a fixed time scale or time drive, so that scheduling continuity and stability are maintained. Reactive scheduling can be divided into predictive–reactive scheduling, full reactive scheduling, and local reactive scheduling. These models are solved by heuristic algorithms, multi-agent simulations, or other artificial intelligence algorithms [8]. Based on the superiority of reactive scheduling, proactive and reactive scheduling were combined, and the baseline scheduling scheme was repaired or re-optimized by reactive scheduling, so that the influence of uncertain factors on the scheduling process was reduced.

Based on the uncertainty of operation in project scheduling and its requirements for scheduling timelines, this chapter focuses on the problem of proactive and reactive scheduling in uncertain environments. Part 2 describes the model variables involved in this chapter. Part 3 analyzes the optimization objectives of multi-project scheduling in uncertain environments. Part 4 establishes proactive and reactive multi-project scheduling models. Part 5 designs a simulated annealing algorithm to solve the problem. In part 6, the conclusions of this paper are presented.

II. LITERATURE REVIEW

In the literature, previous papers on proactive and reactive scheduling mainly focused on project scheduling, production scheduling, port scheduling and so on. For example, He *et al.* [9] analyzed four methods of proactive and reactive scheduling with uncertain disturbances and pointed out that one of the central problems was considering the robustness and quality robustness of solutions in this field simultaneously. Aiming at the robustness of the quality and solution robustness, Zhao *et al.* [10] studied the flow-shop scheduling problem with random failure by the proactive and reactive scheduling theory. Chu *et al.* [11] studied the proactive and reactive scheduling problem of emergency rescue, transforming the problem into the stationary scheduling problem of flexible job shops and designing a genetic algorithm (GA) to solve the problem. Francesco *et al.* [12] studied the proactive and reactive path optimization problem of uncertain information and designed a tabu search algorithm (TSA) to solve the problem. Wu and his collaborators [13] studied the production scheduling problem with uncertain working hours, analyzed the influence of an uncertain duration of key working processes on stability, formulated a proactive and reactive scheduling strategy, established a two-stage proactive and reactive production scheduling model with an uncertain project duration to maximize the robustness of production scheduling, and designed a search algorithm to solve this problem. Lamas and Demeulemeester [14] studied a proactive and reactive scheduling method for the resource-constrained project scheduling problem, the rescheduling strategy is designed which consider the uncertainty project duration. Van *et al.* [15] studied the proactive and reactive scheduling problem with uncertain project duration. The robustness of the scheduling solution was enhanced by setting the buffer time reasonably, and the model of proactive and reactive scheduling with stochastic activity duration was established. Deblaere *et al.* [7] studied the resource-constrained proactive and reactive project scheduling problem, and used a proactive and reactive scheduling policy to predict interference incidents to minimize the negative impact of interference incidents on scheduling costs. Elshaer and Yamamoto [16] studied the time buffering problem of resource-constrained proactive and reactive project scheduling, which copes with multiple interruptions of project scheduling in uncertain environment. Schatteman *et al.* [17] studied proactive scheduling and risk management in construction projects under uncertain environment and designed a heuristic algorithm to obtain the basic plan of proactive scheduling. Olivier and Erik [18] analyzed the influence of interference incidents on the project duration and cost, and time-cost trade-off of stochastic resource-constrained proactive scheduling is studied. De *et al.* [15] studied the project scheduling problem with multiple interferences, the interferences are recovered by setting the buffers, and the multi-interference proactive project scheduling model is designed. Deblaere *et al.* [19] studied the proactive and reactive strategy of resource-constrained project scheduling and made a proactive and reactive scheduling strategy, based on satisfying the resource-constrained and logical relationship, which minimized the uncertain disturbances in relation to the duration and cost of the project. Aiming at the robustness of the optimization of scheduling, Davari and Demeulemeester [20] analyzed the proactive and reactive resource-constrained scheduling problem and indicated that the contribution of the buffer-based reactions is important. Ning *et al.* [21] proposed the proactive and reactive project scheduling problem, aiming at minimizing the maximum cash flow gap of contractors. A proactive and reactive scheduling optimization model for time buffers, added to the baseline scheduling, was established, and a Tabu-simulated annealing search (Tabu-SA) and variable-neighborhood tabu search (VNTS), as well as two hybrid metaheuristic algorithms, were designed to solve this problem. Shen *et al.* [22] studied the proactive and reactive scheduling problem of software developmento'o projects and established a multi-objective dynamic scheduling model considering scheduling cost, duration, robustness and stability, and designed a multi-objective evolutionary algorithm to formulate a proactive and reactive scheduling scheme. Li *et al.* [23] studied a proactive project scheduling problem for stochastic discrete time and cost, a proactive scheduling model is established, based on the robust optimization theory.

Ivanov and Ivanov [24] studied the optimization problem of reactive scheduling, and the adaptive scheduling was designed in order to feed dynamic changes back into the scheduling process. Liu *et al.* [25] analyzed the impact of the disruption of the scheduling process in the supply chain environment and designed an event- driven and cycle-driven hybrid rescheduling method and a Pseudo-polynomial reactive programming algorithm, based on the perspective of multi-objective optimization. Vitoriano *et al.* [26] used the goal planning method to study the reactive scheduling problem. Cost, response period, priority rules and security were considered, which affect the scheduling plan, and a multi-objective optimization model was established. Leung and Chen [27] used delay time and the minimization of the number of vehicles delivered as the goal to study the problem of the reactive scheduling of production and distribution. Battarra *et al.* [28] studied vehicle allocation and dynamic path optimization based on cluster customer service. Xia *et al.* [29] studied the reactive scheduling of transportation and the freight volume matching optimization problem, which considered minimal carbon emissions as the goal. A joint optimization model of vehicle loading and path planning was constructed by Manzini [30], and the problem of just-in-time reactive material distribution scheduling of a mixed flow assembly line was studied. Miao *et al.* [31] studied the problem of vehicle transportation scheduling, with a fixed path, under a multi-transit system, with a time window. Chen *et al.* [32] analyzed energy-efficient scheduling for real-time tasks in an uncertain cloud computing environment.

All the analysis shows that, firstly, by taking the stability of scheduling as the research object, some scholars strive to minimize the deviation between the actual plan and the baseline plan formulated in the uncertain environment. Buffers of the reasonable setting activities are used as the proactive scheduling and reactive scheduling strategy to increase the stability of the project, and multiple heuristic algorithms are used to solve the problem. Secondly, by taking the resource uncertainty of scheduling as the research object, under random resource-constrained, proactive scheduling strategy or reactive scheduling strategy is formulated in order to minimize costs in uncertain environments, which disturbances of duration and cost is minimize under uncertain factors. Thirdly, by taking the robustness of scheduling as the research object, effective buffers are designed in an uncertain environment, so that scheduling efficient is better. On the basis of meet the requirements of active resource constraints and logical relationships. The proactive scheduling and reactive scheduling strategies are designed to minimize interferences of duration and cost in multi-project scheduling.

III. THE BUFFER SETTING STRATEGIES

Based on these analyses, we could determine that proactive and reactive scheduling was based on the historical data, predict the possible uncertain factors in scheduling, and construct the corresponding recovery strategy in advance. In order to improve the robustness of the scheduling system, the proactive and reactive scheduling policy was used to analyze the multi-project scheduling problem in uncertain environments. The countermeasure to deal with an uncertain environment was to set up the reasonable buffer resource and buffer time, so as to deal with interference incidents quickly and minimize the disturbance deviation of multi-project scheduling costs and duration. First, multi-project scheduling problems belong to the resource-constrained project scheduling problems, and the impacts on the resource constraints of a scheduling scheme should be taken into account when making decisions. In view of the uncertain factors in project scheduling [33]–[36], the historical data was analyzed by prediction methods [37], and countermeasures to the causes of interference incidents were formulated. Secondly, it was necessary to determine whether the resource substitution or the resources buffer was allowed in the scheduling scheme in the proactive and reactive scheduling strategy. When there were the buffer resources in the multi-project scheduling system, the availability of resources in multi-project scheduling could be reduced, the buffer resources were allocated in the initial stage, which can effectively deal with the project interference caused by the resource shortage. Finally, one or more time buffers are inserted between the activities of the project to avoid the conflict of resources, and the multi-project scheduling problems with multi-factor disruptions can be effectively solved. Figure. 1 displays the decision-making tree of multi-project proactive scheduling.

Buffer resource setting. Suppose there is a renewable resource, this kind of renewable resource can cause resource interruption, which depends on the duration deviation and the distribution of the recovery scheduling time, after the interruptions. Therefore, it is necessary for the reference scheduling to set a certain buffer resource (or relaxation resource) in order to maintain the continuity of the project. If the buffer source is formulated, the interruptions of one or more resources will not necessarily cause the project schedule to be interrupted. The setting of the resource buffer depends on the historical data. It is necessary to statistically analyze the distribution of available resources and make the reasonable buffer resource according to the data. The buffer resource calculation is as follows:

$$P(a_k = j) = \binom{a_k}{j} A_k^j \, (1 - A_k)^{a_k - j} \tag{1}$$

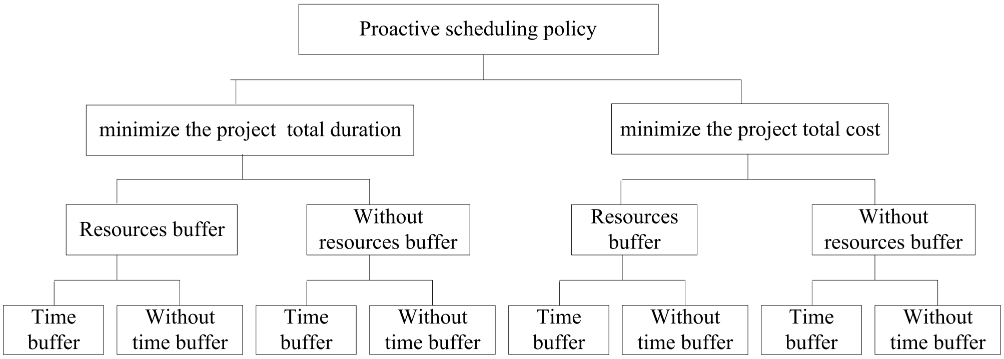

FIGURE 1. **Decision-making tree of multi-project perturbation scheduling.**

$$A_K = \frac{E(X_k)}{E(X_k) + E(Y_k)} \tag{2}$$

$E(X_k)$ represents the distribution of the anticipated interruption time; $E(Y_k)$ represents the distribution of the anticipated recovery time. When the discrete probability distribution of the resource is known, the expected value of the available amount of resources can be determined, and the available amount of the buffer resource is smaller than the maximum amount of used resources. Therefore, it is necessary to establish a scheduling mechanism to limit the maximum of the buffer resource. If the buffer resource exceeded the upper limit of resource availability, the scheduling scheme will be infeasible.

Time buffer setting. If the method of increasing the buffer resource is not adopted, another method is to increase the buffer time. The buffer time is set before the slack time and is then used to proactively and reactively deal with the influence of potential disturbances, such as the interruption of resources or changes in activities in the multi-project scheduling scheme. In order to make the starting time of the activity as early as possible, it is necessary to use the method of iterative right shift in a feasible reference scheduling scheme.

To achieve the minimization of the instability of the project to meet a deadline, the buffer time I_i is inserted before the corresponding activity j. The buffer time is calculated as follows:

$$I_i = \sum_{j=PRED} \omega_{ij} \max\left\{0, s_{i(j-1)} + d_{i(j-1)} + E\left(\Delta_{i(j-1)} + s_{ij}\right)\right\} \tag{3}$$

The symbols used in this article are defined as follows:

IV. ESTABLISH THE MODEL OF PROACTIVE AND REACTIVE MULTI-PROJECT SCHEDULING

A. OPTIMIZATION SUB-MODEL OF PROACTIVE MULTI-PROJECT SCHEDULING

Based on the particularity of proactive and reactive scheduling and its demand for scheduling timeliness, its core goal is to minimize the deviation of scheduling and fully consider the influences on time and cost. According to the above analysis, the proactive multi-project scheduling model is established in uncertain environments as follows (1)–(11), as shown at the bottom of this page.

Formula (4) is an objective function that represents the minimization of the disturbance deviation between the

$$\min G = \eta \sum_{i=1}^{i} E\left(\Delta_i^+ \cdot c_i^+ + \Delta_i^- \cdot c_i^-\right) + (1-\eta) \sum_{i=1}^{i} \sum_{j=1}^{j} \left|S_{ij} - s_{ij}\right| \tag{4}$$

$$s.t.\ \ s_{00} = 0; \tag{5}$$

$$s_{ij} = \Delta_{ij} + \max\left(s_{i(j-1)} + d_{ij}\right), \quad s_{ij} \le \delta,\ \forall i \in N,\ \forall j \in \{1, J\}; \tag{6}$$

$$E_{i(j-1)} + 1 \le E_{ij}, \quad \forall i \in N,\ \forall j \in \{1, J\}; \tag{7}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{J} r_{ijk}^{\rho} \le R_k^{\rho}, \quad \forall i \in N,\ \forall j \in \{1, J\},\ \forall k \in R^{\rho},\ \forall m_i \in M_i; \tag{8}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{J} r_{ij\rho}^{\nu} \le R_{\rho}^{\nu}, \quad \forall i \in N,\ \forall j \in \{1, J\},\ \forall \rho \in R^{\nu},\ \forall m_i \in M_i; \tag{9}$$

$$\sum_{i \in N} \sum_{j \in J} r_{ijmk}^{\rho} \cdot \omega_{imk} \le W_{ijk}^{\rho}, \quad \forall \rho \in R^{\nu},\ \forall k \in K; \tag{10}$$

$$\sum_{i \in N} \sum_{j \in J} r_{ijm\rho}^{\nu} \cdot \omega_{im\rho} \le W_{ij\rho}^{\nu}, \quad \forall \nu \in \left\{0, d_{im_i} - 1\right\},\ \forall \rho \in R^{\nu}; \tag{11}$$

TABLE 1. The symbols used in this article.

i indicates that there are i subprojects in multi-projects
j indicates that the number of activitoes in each subproject
Δ_{ij} indicates that the deviation between the actual completion time and the planned completion time
S_{ij} represents the actual start time of the activity j in the subproject i
s_{ij} represents the planned start time of the activity j in the subproject i
c_i^+ represents the additional cost caused by the deviation of the construction period
c_i^- represents the decreased cost caused by the deviation of the construction period
δ represents the project's deadline
Δ_i^- indicates that the deviation between the completion time and the deadline is negative in the subproject i
Δ_i^+ indicates that the deviation between the completion time and the deadline is positive in the subproject i
r_{ijk} indicates that demand of resource K in activity A_{ij}
$R_k^\rho(k=1,2,\cdots,k)$ indicates that the available amount of renewable resources k
$R_p^v(p=1,2,\cdots,p)$ indicates that the total amount of non-renewable resources p
r_{ijk}^ρ indicates that the demand amount of renewable resources of the activity j in the subproject i
r_{ijp}^v indicates that the total amount of non-renewable resources of the activity j in the subproject i
I_{ij} represents the inserted time buffer of the activity j in the subproject i
$E(X_k)$ represents the distribution of the desired interruption time
$E(Y_k)$ represents the distribution of the expected recovery time
d_{ij} indicates the duration of the activity j of the subproject i
E_{ij} represents the earliest start time of the activity j of the sub-project i
r_{ijmk}^v indicates that the activity j of the sub-project i non-renewable resource requirements under the execution mode m
ω_{imk} indicates that the sub-project i is divided into k stages under the execution mode m, which is at the corresponding stage $\omega_{im}=1$
ω_{imp} indicates that the sub-project i is divided into p stages under the execution mode m , which is at the corresponding stage $\omega_{im}=1$
W_{ijk}^ρ indicates that the demand quantity of activity j of the sub-project i cannot update the demand for resources

TABLE 1. *(Continued.)* The symbols used in this article.

$W_{ij\rho}^v$ indicates that the demthe activity j of the sub-project i cannot update the demand for resources
J represents the number of activities in each subproject
Δ_{ij}^- indicates that the deviation between the actual completion time and the planned completion time is negative
c_{ij}^+ represents the additional cost of the increased caused by the deviation of the construction period
c_{ij}^- represents the additional cost of the reduction caused by the deviation of the construction period
P_{ij} represents the buffer resource of the activity j in the subproject i
s_{00} indicates that the start time of the multi-project scheduling activity is zero
W_{ijk}^ρ indicates that renewable resource requirements of the activity j in the subproject i
W_{ijp}^v indicates that non-renewable resource requirements of the activity j in the subproject i
r_{ijmk}^ρ indicates that renewable resource requirements under the execution mode m of the activity j in the subproject i
ω_{imk} indicates that the subproject i is divided into k stages under the execution mode m, which is at the corresponding stage $\omega_{im}=1$
ω_{imp} indicates that the subproject i is divided into p stages under the execution mode m, which is at the corresponding stage $\omega_{im}=1$
P_i represents the buffer resource of the subproject i
r_{ij} indicates that the added resources of the activity j in the subproject i when interruption occurs

duration and the cost of multi-project scheduling in uncertain environments. The optimization goal is transformed into the effect of minimizing the disturbance on the duration of the multi-project scheduling, when $\eta = 0$. The optimization goal is transformed into the effect of minimizing the disturbance on the cost of the multi-project scheduling, when $\eta = 1$. The value range of η is from 0 to 1, which represents the trade-off decisions, made by decision-maker, between the two objectives of the multi-project scheduling. Formula (5) indicates that the starting time of the multi-project scheduling activity is zero. Formula (6) indicates that the completion time of the multi-project scheduling is before or equal to the deadline of the project. Formula (7) represents the immediate predecessor and successor relationship of the activity, that is, the starting time of the subsequent activity is not equal to the ending time of the immediate predecessor activity. Formula (8) and (9) represent the restrictions on the non-renewable resources and the renewable resources, respectively. Formula (10) indicates that the demand for non-renewable resources by activities cannot exceed the resource demand W^{ρ}_{ijk} given in each stage. Formula (11) indicates that the demand for renewable resources cannot exceed the resource demand $W^{\nu}_{ij\rho}$ given in each stage. In each stage ρ, for all ongoing activities, the total demand for any kind of resource cannot exceed the available amount of that resource.

B. OPTIMIZATION SUB-MODEL OF REACTIVE MULTI-PROJECT SCHEDULING

In reactive scheduling, with the execution of the project, the activity duration upwards to a fixed value and the fixed value may deviate from the expected value in the proactive and reactive schedule, leading to the actual start time of the activity being inconsistent with its baseline start time. Inevitably, the baseline plan will be adjusted. Reactive scheduling can be expressed under the premise of a baseline scheduling plan, which is given, and the actual start time is determined based on the actual duration, minimizing the total amount of buffer resources due to delays of the activity start time. The model established is as follows:

$$Min \sum_{i=1}^{N}\sum_{j=1}^{J} c^{+}_{ij}\left(s_{ij} - S_{ij}\right) \tag{12}$$

$$s.t.\ S^{T}_{ij} = S^{b}_{ij}, \quad \forall i \in N; \tag{13}$$

$$\sum_{j=1}^{J} r_{ij} \leq P_i, \quad \forall i \in N \tag{14}$$

Formula (12) represents the minimization of the total cost of added buffer resources due to the delay of the activity start time. Formula (13) indicates that the start time of the current activity is the start time of the baseline schedule, that the baseline plan is adjusted when each interruption occurs, and that the baseline start time S^{b}_{ij} of the activity should be updated to the new start time S^{T}_{ij}. Formula (14) indicates that the added resources amount is less than the amount of resource buffers. Equations (8)-(11) in the proactive and reactive scheduling model are still applicable in the reactive scheduling model.

The above two sub-models are related through the baseline scheduling. The proactive and reactive model generates a baseline start time for time-buffered activities, which, as a known parameter, is inputted into the reactive model, and an original benchmark is provided to determine the actual start time. According to the actual schedule change, baseline scheduling is adjusted by reactive scheduling in order to make the scheduling feasible.

V. DESIGN GENETIC SIMULATED ANNEALING ALGORITHM

Leus and Herroelen [38] proved that under the uncertain conditions, the stability problem based on the project deadline and discrete interruption is NP-hard. Kolisch *et al.* [39] proved that multi-mode resource-constrained project scheduling problem is also NP-hard. The genetic algorithm and simulated annealing algorithm have been widely used in many research fields [40]–[43], but their defects have also been found in the process of research. For example, in the early stages of the genetic algorithm, a large difference in population individuals led to premature convergence. In the later stage of the algorithm, the small individual difference of population led to the superior individual entering the next generation population, without an obvious advantage in the evolutionary process. Therefore, it was easy to prematurely converge, and the ability of local optimization was poor, which was a disadvantage of the genetic algorithm. However, the simulated annealing algorithm could make up for its defects. The simulated annealing algorithm could effectively avoid falling into the local optimal solution and find the global optimal solution of the objective function by using the Metropolis criterion to optimize the process. Because of its dependence on the initial temperature and other parameters, the global convergence required a higher temperature in the removal process, and the evolution rate was also slow. In this paper, a genetic simulated annealing algorithm was designed by combining the genetic algorithm with the simulated annealing algorithm. The simulated annealing algorithm could control the convergence of the algorithm and avoid falling into the local optimal solution. The two algorithms were combined to form a parallel genetic simulated annealing algorithm, in which only one solution was reserved for each unit of time in the operation to avoid the interference of useless information and historical data in the search process. The combination of a simulated annealing algorithm and genetic algorithm could improve the evolutionary ability, optimization performance and search ability of both. In the genetic simulated annealing algorithm, the crossover and mutation operation preserved the superior individuals of the parents and increased the diversity of the population. The simulated annealing process effectively controlled the convergence of the algorithm, enhanced the global optimization capability of the algorithm and improved the performance of the algorithm. Based on the above analysis, in view of the complexity of the proactive and reactive multi-project scheduling problem in uncertain environments, the genetic simulated annealing algorithm could not only obtain the global optimal solution, but also accelerate the solution speed and efficiency of the algorithm.

To ensure the robustness of the scheduling, which carries on the optimized scheduling aimed the cost and duration minimization. In this chapter, the simulated annealing algorithm and genetic algorithm were integrated effectively, and the genetic simulated annealing algorithm was designed to solve the problem, which improved the performance of the genetic algorithm. In the initial stage of the genetic algorithm, the population of the genetic algorithm was diverse, a partial adjustment is made in the population of the simulated annealing algorithm. In the later stage of the genetic algorithm, When the population is convergent, the search of the genetic algorithm has hysteresis. The simulated annealing algorithm preserved the diversity of the population and avoided premature convergence, caused by the genetic algorithm. Therefore, on the basis of genetic diversity, that is adjusted adaptively according to population diversity. In the genetic simulated annealing algorithm, the probability of selection is determined by the temperature parameter, the higher the temperature parameter, the higher the probability of acceptance. With an increase of the population diversity, the temperature parameters of the population would decrease. The design procedure of the genetic simulated annealing algorithm is shown in Figure 2.

```
Genetic Simulated Annealing  Algorithm
inputs:population-size, number-generations, Pc,Pm, number-interations,a-
cooling factor
outputs:non-dominated-solution-set
procedure
population=generate-initial-population(population-size);
generation-1;
while (generation<number-generations) do
   simulated-annealing-stage(population,number-interations,a);
   mating-pool=parent-selection-process(population);
   offprings=crossover-process(mating-pool,Pc);
   mutation-process(offsprings,Pm);
   population=suvival-selection-process(population,offprings);
   generation=generation+1;
end while
non-dominated-solution-set=get-non-dominated-solutions-
return non-dominated-solution-set;
```

FIGURE 2. Genetic simulated annealing algorithm design.

The steps of the genetic simulated annealing algorithm are as follows:

Coding design: in this paper, multiple sets of coded chromosome structures are selected. The chromosome genes correspond to the activity numbers, and the genes value correspond to a priority list. Natural coding represents the activity priority, and the priority is a natural number between 1-m. The higher the value of the priority, the greater the priority is. In order to ensure the validity of the chromosomes, the one-to-one correspondence between the priority of the activity with the gene must be established, satisfying the requirements of the uniformity of the spatial distribution of the solution and the searching generality.

In order to improve the efficiency of the algorithm, all initial solutions must be feasible solutions, when generating the initial solution. Each feasible solution (AL^{ini}, ML^{ini}, SL^{ini}) is generated according to the representation method of the above solution, in which AL^{ini} indicates that a list of activity orders is randomly generated under logical relationship constraints; SL^{ini} means that, on the time margin list, all ε_i are defined as 0; and ML^{ini} indicates that each activity randomly selects an execution mode.

Fitness function: the fitness function reflects the quality of the solved feasible solution. The fitness function is designed as $fit\,(t)$, $fit\,(t) = G\,(t)$, in which the target value of the individual is represented by $G\,(t)$, so the larger the fitness function value, the better the individual.

Selection operator: the parental selection process is used to decide a feasible solution that constitutes the crossing pool population, which is used to generate new feasible solutions in the selection operator. Two feasible solutions in the population are selected randomly, and the better of the two is incorporated into the crossing pool. To achieve this, repetitive operation should be performed, until the number of populations in the crossing pool reaches M, where M is the population size.

Crossover operator: the crossover probability P_c is set, and two insertion points C_1 and C_2, $1 \leq C_1 < C_2 < N$, are selected randomly, exchanging the substring between two points. After deleting the same location coding of the parental activity list, we copy it onto the offspring in accordance with the original coding sequence. If an offspring activity list coding that violates the constraint is generated, the cross-in position will be adjusted.

Mutation operator: for the mutation operation of a given list of activities, the location of the activity is set as $p = 1, \cdots, N-1$. If there is no predecessor and successor relationship between p and $p+1$, we need to select the location of p and $p+1$ with the mutation probability P_m, performing the mutation operation. Performed by the mutation probability P_m by mutating the activity sequence at any position, the mutation operation for the priority of the activity is a random reset process, generating a new activity sequence.

Buffer change operator: For the current buffer list SL^{ini}, select an activity to set its buffer value ε_i to a value in the interval $[0, L_{im} - E_{im}]$. The adjacent vertex SL^{imi} of the current solution is generated, and ML^{ini} and SL^{ini} remain invariant, which are denoted by AL^{dmd} and ML^{dmd}.

Annealing process: the optimal feasible solution of the activity will be preserved during this process. The parental population is replaced with the new population, generated by the operation, and the fitness value of the chromosome is recalculated. If the fitness value of the new population is higher than that of the best, the chromosomes corresponding to the new fitness value will be replaced with the original optimal chromosomes.

The acceptance probability of the annealing process: the proportional cooling method is used in this paper. The annealing cooling function is $t_{k+1} = t_k \cdot r$, and the decay factor is $r = 0.95$. We assume that the solution p is the current solution, of which the solution q is the neighborhood solution, and Δf is the incremental target value. If $\Delta f < 0$, the algorithm moves from p to q; and if $\Delta f > 0$, the probability P_{pq} is used to determine whether it moves or not.

Termination condition: when the annealing temperature is $t_f = 60°C$, the annealing process reaches an inner equilibrium state, and the operation stops.

VI. EXPERMENT AND SIMULATION

A. SIMULATION TESTS

The actual case data is analyzed to study the proactive and reactive and reactive scheduling problem in this chapter.

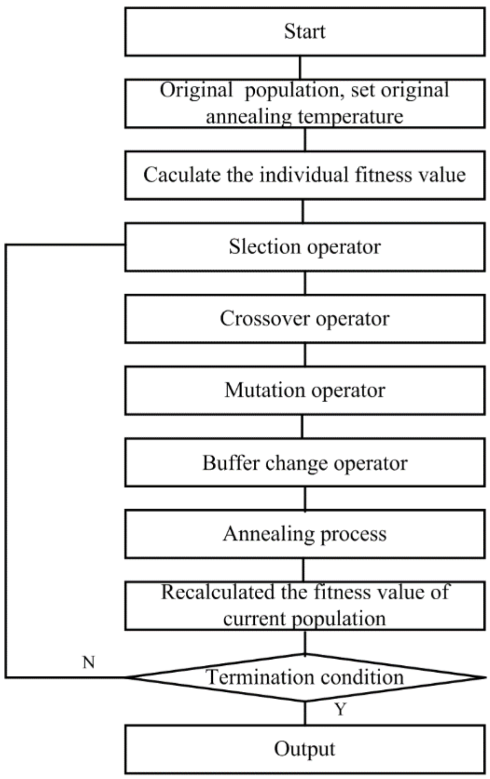

FIGURE 3. Genetic simulated annealing algorithm flow.

TABLE 2. Duration and cost information on proactive and reactive multi-project scheduling.

Activity	d_{ij}	C	Activity	d_{ij}	C	Activity	d_{ij}	C
A_{11}	3	15	A_{21}	1	6	A_{31}	2	6
A_{12}	2	10	A_{22}	2	8	A_{32}	2	8
A_{13}	3	9	A_{23}	2	11	A_{33}	3	12
A_{14}	2	12	A_{24}	3	9	A_{34}	2	15
A_{15}	2	4	A_{25}	2	14	A_{35}	3	12
A_{16}	1	6	A_{26}	3	8	A_{36}	3	15
A_{17}	3	9	A_{27}	2	13			
			A_{28}	3	15			
			A_{29}	4	7			
			A_{210}	3	12			

The optimization model of proactive and reactive and reactive scheduling is established in uncertain environments, and the genetic simulated annealing algorithm is used to simulate the experiment. Each activity represents the corresponding working procedure, and the relevant information of the activity is shown in table 2, which includes 28 activities, virtual start activities and virtual end activities. There are 7 kinds of resources, including 4 kinds of renewable resources and 3 kinds of non-renewable resources. The relationship between multi-project activities is shown in figure 4. The budget of

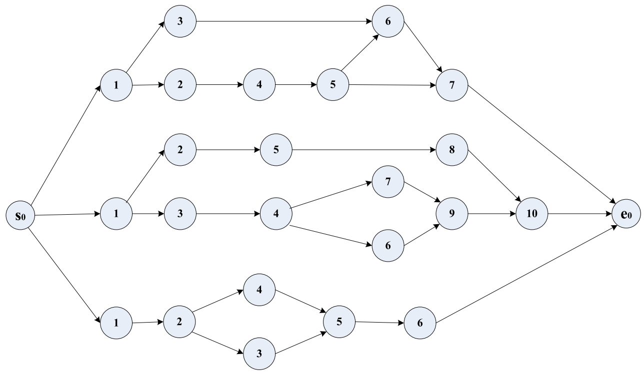

FIGURE 4. Multi-project network diagram.

the proactive and reactive multi-project scheduling is 260, the duration of the proactive and reactive scheduling is D = 20, and the weight proportion is $\eta = 0.5$, between the two objectives of the total cost and the total duration in multi-project.

TABLE 3. Time buffer and resource buffer of proactive and reactive multi-project scheduling.

activity	P	I	activity	P	I	activity	P	I
A_{11}	5	6	A_{21}	2	4	A_{31}	5	4
A_{12}	5	5	A_{22}	2	5	A_{32}	5	4
A_{13}	8	0	A_{23}	2	5	A_{33}	5	4
A_{14}	5	6	A_{24}	2	0	A_{34}	6	3
A_{15}	6	0	A_{25}	2	4	A_{35}	5	0
A_{16}	8	2	A_{26}	2	4	A_{36}	5	3
A_{17}	5	2	A_{27}	2	0			
			A_{28}	2	7			
			A_{29}	2	0			
			A_{210}	2	3			

The genetic simulated annealing algorithm is programmed by MATLAB, and the established model is solved. The total cost of the proactive and reactive multi-project scheduling project is 236. The total duration of the multi-project scheduling meets the prescribed deadline and remains within the limit of the total budget of 260. Table 1 displays duration and cost information relating to the proactive and reactive multi-project scheduling. Table 3 shows the buffer time and buffer resources of the activities related to the proactive and reactive multi-project scheduling, which shows that the proactive and reactive multi-project scheduling possesses good robustness, and the value of the object function is $\prod = -9.8$.

Due to the uncertainty of the scheduling, proactive and reactive and reactive scheduling attaches more importance to the total cost and total duration. The weight distribution coefficient η of the two optimizing targets is a key parameter. In order to analyze its impact on the proactive and reactive

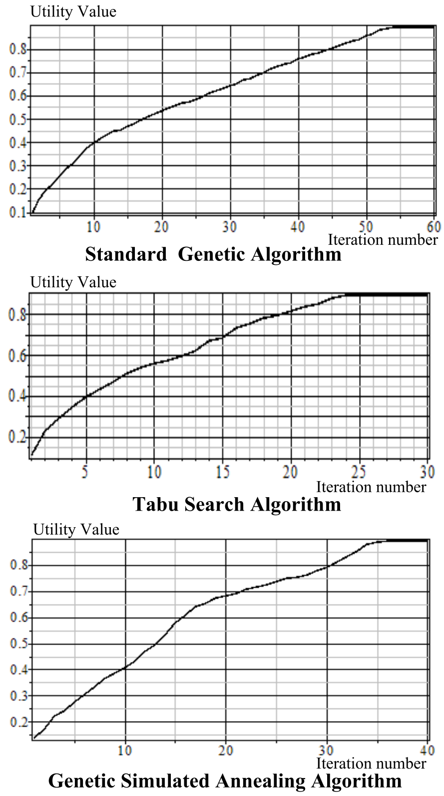

FIGURE 5. The contrast diagram of algorithm convergences.

TABLE 4. $\eta = 0.3$ Proactive and reactive multi-project scheduling computation.

			Random scheduling	Based scheduling	GASA
Without time buffer	Without resource buffer	Minimize cost	1348.55	325.56	276.60
		Minimize duration	1004.60	225.60	177.90
	Resource buffer	Minimize cost	612.55	122.50	112.20
		Minimize duration	524.10	104.00	76.50
Time buffer	Without resource buffer	Minimize cost	1080.30	234.50	208.35
		Minimize duration	746.20	152.70	140.10
	Resource buffer	Minimize cost	541.10	107.35	96.50
		Minimize duration	376.10	80.70	72.60
		Average	*779.19*	*169.11*	*145.09*

scheduling objective function in uncertain environments, the results of the proactive and reactive multi-project scheduling are analyzed, when $\eta = 0.3$, $\eta = 0.5$, and $\eta = 0.6$, and the other parameters are invariant. Table 4, Table 5 and Table 6 present the corresponding analysis results.

TABLE 5. $\eta = 0.5$ Proactive and reactive multi-project scheduling computation.

			Random scheduling	Based scheduling	GASA
Without time buffer	Without resource buffer	Minimize cost	1117.40	296.50	239.30
		Minimize duration	1011.30	243.90	198.80
	Resource buffer	Minimize cost	477.40	96.75	80.80
		Minimize duration	433.40	82.90	67.80
Time buffer	Without resource buffer	Minimize cost	707.85	141.65	121.35
		Minimize duration	711.40	145.90	128.80
	Resource buffer	Minimize cost	293.15	53.65	49.10
		Minimize duration	333.30	55.40	48.00
		Average	*635.65*	*139.58*	*116.74*

TABLE 6. $\eta = 0.6$ proactive and reactive multi-project scheduling computation.

			Random scheduling	Based scheduling	GASA
Without time buffer	Without resource buffer	Minimize cost	1025.15	296.50	232.30
		Minimize duration	866.30	234.40	188.00
	Resource buffer	Minimize cost	393.05	93.85	78.65
		Minimize duration	322.60	68.50	55.10
Time buffer	Without resource buffer	Minimize cost	502.20	104.35	95.90
		Minimize duration	486.40	97.10	87.60
	Resource buffer	Minimize cost	173.15	39.85	36.10
		Minimize duration	173.90	35.60	29.20
		Average	*492.72*	*121.27*	*100.36*

Based on the study of the proactive and reactive scheduling strategy to predict the possible start time of each activity, the effect of uncertain factors on the disturbance deviation c_{ij} of the cost and duration Δ_{ij} of each activity can be predicted. Under the premise of not exceeding the project cost budget and project deadline, the total cost and total duration are minimized in proactive and reactive scheduling. From the above analysis, it can be concluded that, with the increase of cost, the duration of the project gradually decreases, and with the increase of $\sum_{i=1}^{i} E\left(\Delta_i^+ \cdot c_i^+ + \Delta_i^- \cdot c_i^-\right)$, the impact of disturbance incidents on the proactive and reactive scheduling targets shows a monotonous decreasing trend.

B. COMPARATIVE ANALYSIS OF DYNAMIC SCHEDULING AND PROACTIVE AND REACTIVE-REACTIVE SCHEDULING

In this paper, the proactive and reactive multi-project scheduling problem is proposed, and we download the standard study from the project scheduling problem website, http://129.187.106.231/psplib/, take PSPLIB data, J10, J20 and J30, as examples, and use dynamic scheduling and proactive and reactive scheduling to test them (see Table 7 for details). MPDSP(%) (Multi-project Dynamic Scheduling Problems, MPDSP for short) represents the average deviation of the scheduling, based on MPDSP; MPPRSP(%) (proactive and reactive multi-project and reactive scheduling problems, MPPRSP for short) represents the average deviation of the scheduling, based on MPPRSP; Impr.(%) indicates the improvement of the average completion time of A, relative to B; BETTER indicates the improvement of the proactive and reactive scheduling scheme on the dynamic scheduling scheme; EDUAL indicates similarity between the proactive and reactive scheduling scheme to the dynamic scheduling scheme; WORSE indicates the degree to which the proactive and reactive scheduling scheme is worse than the dynamic scheduling scheme. As can be seen from Table 7, the duration and resource availability is closely related under resource constraints, and the duration is shortened significantly under the proactive and reactive scheduling mode.

TABLE 7. Comparative results of dynamic scheduling and proactive and reactive-reactive scheduling.

	MRCPSP(%)	NP-MRCPSP(%)	Impr. (%)	BETTER	EQUAL	WORSE
J10	32.27	31.54	0.49	47	488	1
J20	17.76	17.03	0.55	99	432	23
J30	13.75	13.23	0.41	108	404	40
J10[1]	15.49	14.94	0.42	36	500	0
J20[1]	8.27	7.61	0.53	68	486	0
J30[1]	5.6	5.06	0.44	74	478	0

C. COMPARATIVE ANALYSIS OF ALGORITHMS

In this paper, the standard genetic algorithm, Tabu search algorithm and genetic simulated annealing algorithm are used to analyze the above examples in order to test the performance of the genetic simulated annealing algorithm. The convergence of the calculation results, using above algorithms, is shown in Figure 5.

It can be seen, from Figure 5, that the Tabu search algorithm has the fastest convergence rate, but it is easy to generate a local optimal solution. While the convergence rate of the genetic simulated annealing algorithm is slower than the Tabu search algorithm, its decreased speed of convergence is the fastest. Therefore, its global convergence ability is the strongest among the three. Moreover, in order to verify the validity of the algorithm, the above example is calculated 20 times to calculate the optimal value, the worst value and the average value, and the calculation results are shown in Table 8.

TABLE 8. Comparative analysis of simulation resoults.

Algorithm	Simulation experiment results					
	The optimal value	Worst value	Average value	Calculating time	Search success rate	Average search iterations
Standard genethic algorithm	0.809	0.1	0.643	12.2	32%	53.31
Tabu search algorithm	0.809	0.11	0.706	16.5	31%	25.32
Genetic simulated annealing algorithm	0.809	0.14	0.753	8.9	47%	34.36

The data of Table 8 are analyzed. It is found that the genetic simulated annealing algorithm has the highest search success rate, and the Tabu search algorithm has the lowest search success rate. In the calculation results of the genetic simulated annealing algorithm, the worst value and the average value are the best of the three algorithms. This proves that the genetic simulated annealing algorithm has the strongest global search ability.

For the proactive and reactive multi-project scheduling problem in uncertain environments, the above three algorithms can calculate the better solution. However, interference incidents lead to activity disruption in uncertain environments, and the buffer change operator (SC) and crossover operator are designed in the genetic simulated annealing algorithm. This means that, in the early stages of the algorithm, the optimum individual is produced as soon as possible, the optimum individual is protected, and the algorithm has a strong capability of global search. Application examples show that the genetic simulated annealing algorithm is more efficient and robust than the two other algorithms.

VII. CONCLUSION

In this paper, the proactive and reactive multi-project scheduling problem was proposed. First, we defined the problems studied, analyzed the interference incidents based on historical data, a baseline scheduling is formulated, the potential interference incidents are predicted, and the recovery strategy is formulated. The goal was to minimize the duration and cost, which cause by the interference incidents in uncertain environments. Based on the establishment of proactive and reactive multi-project scheduling in uncertain environments, from the computed examples, a scientifically rational buffer of multi-project scheduling is designed, so that it can effectively recover the interference in the scheduling system. When the activity is interrupted, the reactive scheduling mode is adopted, and buffer resources are used, in order to quickly recover the project operation. It could also achieve the goal of minimizing disturbances relating to the schedule duration and cost, which are caused by disturbance incidents. Based on the above analysis, the following conclusions were drawn:

First, according to the characteristics of the proactive and reactive scheduling problem in uncertain environments, this paper analyzed the recovery strategy of proactive and reactive scheduling, after disturbance incidents occurred, and constructed an optimization model, aiming at minimizing the cost and duration of disturbances. A proactive scheduling sub-model is constructed. When the activity is interrupted, the proactive scheduling scheme is used as the basement scheduling scheme, which is embedded into the reactive scheduling, targeting the minimization of the total cost of adding resources, and the reactive scheduling sub-model is established.

Second, the study shows that it is no simple linear relationship between the stability of proactive scheduling and the total cost of the project, but it is related to the resource cost of adding the buffer. The results show that adding buffers can reduce the impact of interference incidents in scheduling, but it is at the cost of increasing the resources cost.

Finally, the genetic simulated annealing algorithm was designed to solve the problem. In the genetic simulated annealing algorithm, the crossover and mutation operation retained excellent individuals of the parent generation and increased the diversity of the population. The simulated annealing process effectively controlled the convergence of the algorithm. The global optimization ability was enhanced, and the performance of the algorithm was improved.

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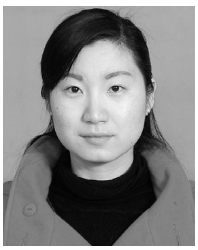

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