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USING HYBRID SIMULATED ANNEALING ALGORITHM IN RESOURCE CONSTRAINED PROJECT SCHEDULING PROBLEM

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Abstract

Mostly the way of solving resource constrained project scheduling problem (RCPSP) will rely on implementing mathematical modeling. However, it often results in the low efficiency of solution searching. Therefore, exploring a more efficient alterative to solve the RCPSP is the main objective of the paper. Simulated Annealing (SA) has been proven an excellent heuristic technique of neighborhood search for solving combinatorial optimization problems in various fields. However, simple SA algorithm cannot guarantee to obtain a better solution quality on solving the combinatorial optimization problem compared with the other heuristic techniques. To enhance the quality and efficiency of solution searching, the paper presents a hybrid SA based algorithm to solve the RCPSP and a program with a good user interface which can link with a well known project management software-Microsoft Project 2000. The outcome of using the algorithm to solve the RCPSP has been shown better than other heuristic techniques after cases experiment.

Keywords: resource constrained, Simulated Annealing, optimization

Introduction

Construction projects are scheduled by the way of the Program Evaluation and Review Technique (PERT) and the Critical Path Method (CPM) which were developed successfully. Although PERT/CPM and other related scheduling technologies have already been widely applied in the project planning and control problem, PERT/CPM plans the project operation scheduling only in respect to the aspect of time without considering the factor of resource, cost, and finance constraints. Thus, for the more complicated and large-scale projects, it is impractical if the factor of resource constraints as well as other factors was not considered in the project scheduling problem. In recent years, due to the growing scarcity of resources, it has become pertinent to discuss how to most efficiently utilize the constrained resources in a project to reduce some unnecessary cost, and obtain the largest economic value. Therefore, the construction time interval of each activity for the project must be efficiently arranged. Thus, such the problem described above could be defined as resource constrained project scheduling problem (RCPSP). There are numbers of researches presented while RCPSP is presented by Kelley since 1963 [10]. These researches can deal with simpler scheduling problems and got some achievement. However, due to the complexity of RCPSP with multi resource type in practice, fewer researches investigated especially in the related problems of the construction project. Such problems are more important and practical in most situations. Therefore, exploring the combinatorial optimization algorithm to solve RCPSP in the construction project is the motivation of conducting this research.

RCPSP is generally a NP-Hard problem. In the early stage, during the solving of the RCPSP, most studies still used to utilize the heuristic method to solve the RCPSP problem. It was found that the solution quality was sometimes worse using the heuristic rules and the preferred solution was not often achieved. Instead of using heuristic method, using mathematics model to solve the RCPSP is the other way for some researchers. The optimal solution can be obtained using the mathematics model; however, it may result in much longer execution time to find the optimal solution of the RCPSP.

Also, according to Wiest's study, the 0-1 integer programming was used to establish a problem with 55 operations and 4 kinds of resource types, which this problem required 1,650 decision variables and 6,870 restrict equations. What's more, there are easily hundreds of operations in the actual environment which would make it almost impossible to solve this kind of the problem and achieve the optimal solution [13].

Therefore, in recent years, some researchers and practitioners have presented lots of new algorithms for the related studies of the RCPSP to improve the shortages of traditional algorithm. Lots of studies have applied the heuristic rule to solve RCPSP, and also developed a lot of heuristic algorithms. One of the well-known heuristic algorithms was first presented by Kelly who brought forth the Serial method and the Parallel method in 1963 [10] and applied to solve the RCPSP. And the subsequent studies of the heuristic method have mainly taken Kelley's heuristic method as its basis and improved the method, such as MINLST Model (Moder and Phillips, 1964) [11], MINSLK Model (Davis and Patterson, 1975) [4], three-Heuristic Model (Boctor, 1990) and other solution technologies [6]. Boctor (1990) and Padilla and Carr (1991) implemented heuristic methods that produce feasible solutions efficiently [5] [6], however, which are not necessarily optimal. In recent years, the studies of solving the RCPSP using AI based algorithms also been paid more attention, and some research findings were also achieved. Karaa, Nasr (1986) [8] and Savian et al. (1996, 1998) implemented neural network (NN) solving construction resource leveling The objective of the model the research presented was to make the resource requirements as smooth as possible [2] [3].

Chan et al. (1996) proposed a algorithm using genetic algorithm (GA) considered solving RCPSP [22]. Yang (1996) applied the constraint programming to solve this problem and made tests for different objectives. These objectives were reached with the shortest finish time and the lower cost [21]. Hegazy (1999) also presented an optimization model using genetic algorithms solving RCPSP [20], too. Leu et al. (1999) solves the RCPSP using GA based a fuzzy optimal model. The model took into consideration both uncertain activity duration and resource constraints [17]. Adeli and Senouci (2001) presented a mathematical model for solving RCPSP, and project total cost minimization simultaneously [16].

Besides the algorithms above have been chosen to solve the RCPSP, there were also some other remarkable achievements for the application of the heuristic algorithms, one of a well-known AI based heuristic algorithm, Simulated Annealing (SA), which is implemented based on this purpose. A brief description of some necessary background is provided as follows:

SA was first presented in 1953 by Metropolis [14] to simulate the cooling of material in heat bath- a process known as annealing and implemented by Kirkpatrick in 1983 [18] for solving Traveling Salesman Problem (TSP), placement, and wiring problem, and showed good performance in solving such problems. Compared with two other heuristic algorithms, Genetic Algorithm and Tabu Search, SA was presented earlier and didn't get attention by other researches.

Until Kirkpatrick presented the whole theory of SA, there are more SA applications presented [18]. The related studies will be described as follows: Wright utilized SA to solve cargo- scheduling problem in 1989 that showed SA has higher solution quality than other heuristic algorithms. In 1993, Jeffcoat and Bulfin utilized SA and neighborhood-searching algorithm to solve resource constrained scheduling problem [1]. Its results showed utilizing SA has better solution quality than utilizing neighborhood search algorithm. In 1996, Boctor utilized SA to solve varied kinds of resource constrained project scheduling problem [7]. Its results showed SA can get a better solution quality than other heuristic algorithms.

In 1999, Skibniewski utilized local optimum algorithm and SA to develop a multi heuristic model to solve resource-leveling problem [12]. Its results showed the model can help obtain god reasonable solution and the model can be implemented in more complex scheduling problem. It could be observed that SA is an excellent heuristic algorithm that could be implemented to solve RCPSP.

However, compared with other AI based heuristic algorithm, simple SA can not guarantee to get a better solution of RCPSP compared with other heuristic algorithms. One of the reasons not get a better solution of RCPSP is to ignore the impact of the selection of "starting solution". The suitability of selecting the initial solution will relate to the solution searching quality of RCPSP. Also, the quality of SA algorithm programming cannot be ignored when exploring to solve the RCPSP. Therefore, the objective of this study was to investigate a hybrid SA based algorithm and implement it to solve the RCPSP. Based on the purpose above, besides this paper proposed an improved SA based model, the paper also presented a program using well-known software-Visual Basic to solve the RCPSP in construction which can help the user implemented the model easily in practice.

Using the Simulated Annealing as the Algorithm to Establish the Structure of the RCPSP Model

The concept that form the basis of SA were published by Metropolis in 1953 in an algorithm to simulate the cooling of material in a heat bath- a process known as annealing. Metropolis's algorithm simulates the change in energy of the system that subjected to a cooling process [18], until it converges to a steady frozen state. Kirkpatrick suggested that this type of simulation could be used to search the feasible solutions of an optimization problem, with the objective of converging to an optimal solution. This approach can be regarded as a variant of the well-known heuristic technique of local search, where a subset of the feasible solutions is explored by repeatedly moving the current solution to a neighboring solution. The SA is one of the Probability Hill-Climbing Search Algorithms, which combines the method of Steepest Descent and the way of searching the optimal value of objective function randomly and globally. In this section, the SA algorithm will be described as follows:

Elements of Simulated Algorithm

The main elements of the SA can be divided into the following items, which are respectively described as follows (Ahuja, 1994) [15]:

(1) Starting Solution;
(2) Neighborhood Solution is derived from the original feasible solutions by searching with the setting move mode and conforms to the problem constraints;
(3) Acceptance probability is the probability which the neighborhood solution can move. The probability can be summarized by $\exp^{-(E2-E1)/kT}$, where E1 is the cost of the current configuration and E2 is the cost of the changed configuration;
(4) The set of configurations, or states, of the system;
(5) A generation rule for new configurations, which is usually obtained by defining the neighborhood of each configuration and choosing the next configuration randomly from the neighborhood of the current one;
(6) The target means objective function;
(7) The cooling schedule of the control parameter includes initial values and rules for when and how to change it;
(8) The termination condition is usu-

ally based on the time and the values of the cost function and/or the control parameter.

The following sections focus on investigating the application of the SA algorithm in RCPSP. The process of the algorithm created in this research will then be introduced.

Establish the objective values and objective functions

This model the paper presented included two objective functions: (1) the minimal total project duration; (2) the smoothest daily resource consumption. If two scheduling have the same first objective value, the second objective value shall be considered, which the smoother one is the optimal value after competing.

The objective functions for the RCPSP optimization model are:
Objective function 1:

$$Min\{Max\ F_i\} \qquad \text{(equation 2. 1)}$$

$$\begin{aligned} S.T.\quad & S_i = MAX\ F_{bi} \qquad \text{(equation 2. 2)} \\ & F_i = S_i + T_i \\ & R_{kj} \leq C_{kj} \end{aligned}$$

i: identification number of each activity of the project.
b: identification number of the precedent activity of the project .
j identification umber of each resource type.
k: the kth day.
F_i: the early finish time of activity i on the condition of resource constraints.
F_{bi}: the early finish time of the previous activity b of the operation i on the condition of resource constraints.
S_i: the early start time of the activity i on the condition of resource constraints.
T_i: the duration of the activity i.
R_{kj}: the quantity demanded of the resource j on the kth day.
C_{kj}: the quantity constrained of the resource j on the kth day.

Objective function 2:

$$Min \sum_{j=1}^{m} \{[\sum_{i=1}^{n} R_{ij}^{2} + \sum_{i=2}^{n} (R_{ij} - R_{(i-1)j})^{2}] \times W_j\} \qquad \text{(equation 2. 3)}$$

i: the ith working day
j: identification Number of each resource project
R_{ij}: quantity demanded of the resource j on the ith working day
W_j: weight of the resource j (its value is determined according to its importance of the resource)
n: total project duration on the condition of the resource constraints
m: all resource days of the project

When considering the RCPSP with multi-resource types, a weight is generally added in order to decide the sequence of leveling, which a weight representing its importance is got to decide the priority of leveling/ smoothing according to the various importance of each resource (such as: cost).

For the objective function 2, it shall conform to all constraint conditions above and make the daily resource consumption as smooth as possible. The least squares method shall be applied to calculate the consumption, and a difference between the daily resource consumption and the resource consumption of the last day will be added to the calculation as an amplification factor. The difference is used to select the optimal daily resource consumption and enable it to reach the optimum use of resources.

The Starting Solution of Simulated Annealing (SA) Algorithm that under the Resources Distribution

Starting Solution in SA is the solution which derived from the most original feasible solutions. The Starting solution of the Simulated Annealing (SA) usually uses a random approach to obtain its initiate feasible solution. The random approach obtaining the starting solution in SA algorithm cannot guarantee to obtain good quality of the solution in combinatorial optimization problem. also, within the previous researches, the SA has been brought up as well as been proven that by using a better starting solution, it can lead the solving quality convergent to the near-optimal solution more quickly [1]. Therefore, finding the other approach to obtain the starting solution for SA is one of the other important issues in the paper.

In the 8 kinds of heuristic methods solving the combinatorial optimization problem presented by Moder [5], the probability of finding the optimal solution by using the MINSLK method is the highest (29%), and thus this method is widely used. The next is the LFT method (20%), and the lowest is the MJP method (1%), shown in Figure 4. The average increased optimal time limit when using the MINSLK method is about 5. 6%, which is also the method that obtains the minimal activity time for the average increased optimal time limit. In addition, based on previous studies [4], MINSLK has been proved as an efficient way to obtain the solution with good quality than using other heuristic algorithm approaches. Therefore, this research has adopted the MINSLK to determine the starting solution for the priority of resource distribution in proper sequence. The sorting structure of starting solution is shown in Figure 1, with the solving process of the MINSLK algorithm (Erenguc, 2003) [19] being explained as follow, as well as its process being shown in Figure 1. (Note: See all figures at the end of this article.)

Step 1: The finished time point of each activity only considers the priority relationship for the qualified (eligible) activity.

Step 2: If there's no occurrence of resource conflict, then arrange all qualified activities to the starting time point and proceed to the finished time point of next activity.

Step 3: If there's any occurrence of resource conflict, then re-calculate the float of all qualified activities and carry on to proceed the scheduling activity with using the minimum float till the occurrence of resource conflict.
Step 4: Advance the shifting time to next finished time point.
Step 5: Continually comply with the abovementioned procedures till all activities have been scheduled.
Step 6: In terms of updating the float, within the most initial float and the latest time of all activities that obtained from the initial scheduling, to calculate the float of the latest time and current time for each qualified activity, which is also known as updating the float value.

Setup Of Major Parameters Of Simulated Annealing-Based Model

This section mainly describes the major parameters of model that is applied on the RCPSP.

Logical Determination of Initial Temperature and Neighborhood Solution

The initial temperature is the initial highest temperature value during the annealing process. Initial temperature have to be large enough to enable the algorithm's initial feasible solution to have enough space to transfer without falling into the local optimal solution; however, it also cannot be so large to avoid time wasting in searching solution space, which might decrease the solution searching efficiency. Kirkpatrick et al (1983) [18] set the default temperature T_0=10 and proposed that the solution quality and processing time of SA can be increased with the use of a better starting solution. As a result, this research used 10 as the initial testing value of temperature.

Swap Move and Insert Move, the move strategy of the neighborhood solution searching for the Simulated Annealing (SA) in this research; have already been illustrated in the earlier section. The logical determining method of neighborhood solution is adopted as the prior inspection of the logical relationship and it can only then be the candidate solution when satisfying the logical relationship. In solving the RCPSP, the objective value is the shortest duration; therefore, it needs to re-conduct the move determination if it does not comply with the logical relationship.

The Maximum Chain Length and Temperature Decreasing Rate

The maximum chain length is the Markov Chain Length, which Kirkpatrick et al. (1983) [18] suggested its length to be the multiple of the number of decision variables; and this paper sets two times of the number of decision variables as its maximum chain length. The temperature decreasing rate, as known as the cooling rate, (α) must be between 0 and 1, while, in general the conventional recommendation is only between 0. 8~ 0. 99, with the SA search having good results; this research adopted 0. 85 to be the default value of α .

Stopping Criterion

The stopping criterion of SA possessed a considerably flexibility stopping criterion. Conforming to the target as we searched for the criterion, we define the stopping criterion into 2 points, and stops proceed of the algorithm while satisfying any point of these 2 points.

(1) Final Temperature: The research of Kirkpatrick *et*. [18] al. didn't determine a specific value on the final value of temperature, but only stop implementing the algorithm when a few invariable solutions that is solved from the last few Markov Chains is obtained. In addition, this research also adopted the setup method of the Kirkpatrick's research for the final temperature value: The setup of its final temperature value adopted the frozen temperature setup, which is directly set to stop the annealing process when temperature T decreased to the temperature that is lower than 0. 0005. Because it has almost reached the frozen state when T value is lower than 0. 0005, thus the inferior neighborhood solution cannot be accepted in such research; however, due to the characteristic this research adopted, as the temperature is decreased to 0. 05, it can then be effectively convergent to the optimal solution or near-optimal solution.

(2) The maximum number of algorithmic times which is unable to improve the target value: it indicates that the number of occurrence for the same target value in the algorithm process reached a certain number and then stop implementing the algorithm, however, for this research, the maximum number of algorithmic times being unable to improve the target value is set at 40.

Computation procedure of the RCPSP

This section introduces the application of the Simulated Annealing on the algorithm procedure of resource allocation as shown below, and its flowchart is shown in Figure 2:

Step 1: Setup each parameter value such as the initial temperature (T_0), temperature decreasing function (α), final temperature (T_e), maximum number of unimproved cycle, etc. ;

Step 2: Use MINSLK to calculate the Target Function 1 to obtain an initial feasible solution $C(X_0)$ and a starting solution scheduling X_0 which make up the current optimal solution $X^* = X_0$, and subsequently the target value of then current optimal solution is $C(X^*) = C(X_0)$, at this moment, it is in the initial status and its initial temperature is T_0;

Step 3: Use the current solution (temporary optimal solution) to schedule X^* according to the neighborhood solution structure, select any 2 points of random numbers to exchange, and determine whether the order conforms to the logical relationship after being exchanged, if not, select other 2 points to exchange again till it conforms to the logical relationship of the scheduling X', and then calculate its Objective's Function 1's value $C(X')$;

Step 4: Calculate the difference of target function $\Delta E = C(X') - C(X^*)$ between the current solution's target value $C(X^*)$ and the neighborhood solution's target value $C(X')$;

if $\Delta E < 0$, then the neighborhood solution $C(X')$ will substitute the current solution as a new $C(X^*)$;

if $\Delta E = 0$, it indicates that $C(X')$ is equal to $C(X^*)$, then calculate the target value of Target Function 2; use the smallest M value as the current solution $C(X^*)$, if the M values are also equal to each other, then use the $C(X')$ to replace the current solution as a new $C(X^*)$;

if $\Delta E > 0$, it indicates the Neighborhood Solution as being greater than the Current Solution, and subsequently a random umber u which is between 0 and 1 will be generated; if u < acceptance probability, $\exp(-\Delta E/T)$, such Neighborhood Solution is then accepted as a new solution; if u > $\exp(-\Delta E/T)$, then such Neighborhood solution is rejected, and return to the Step 3 for continual searching;

Step 5: Under this temperature, repeat Step 4 till the frequency of searching feasible solution reach the maximum chain length, then proceed the process of temperature-shift, the temperature-shift function is $T(K+1) = \alpha \cdot T(K)$;

Step 6: Calculate the new temperature $T(K+1)$, repeat Step 3~5;

Step 7: Check the stop condition, whether it has reached the set condition, if not, repeat Step3~6 till it meet the stop condition.

Summary

Even the concept of SA can be effectively applied on solving the problem of the combinatorial- optimization, however, there is no such commercial software which can solve the RCPSP. Also, using the conventional SA algorithm still can not guarantee to obtain the better quality of searching solution on the RCPSP.

Based on the purpose above, this paper proposed an improved SA based model to solve the RCPSP. In order to prove the model the paper presented is able to easier and effectively solve and obtains the optimal solution or near-optimal solution. Furthermore, it also can greatly improve the complicated rules and procedures of the conventional algorithm. In the next section, the performance and practicality of the model the paper presented will be illustrated with the empirical cases experiment. .

Cases Experiment

In this research, the research used Microsoft Visual Basic 6. 0 as the program development tool and combining it with Microsoft Project 2000 software, the analysis and computation model established in this research will be programmed to take subsequent positive cases and sensitivity analysis. Program introduction to programs is shown respectively as Figures 3, 4, 5 and 6, which are program menus written by VB6. 0 for this research. First of all, the user opened the basic data of the project created by MS Project, shown in Figure 3. 1. Secondly, the user set those necessary model's parameters, such as initial temperature (T_0), temperature decreasing rate (α), Markov Chain Length (L) and final temperature (Te) etc. When inputting is completed, select "Compute allocation or leveling" and begin to compute, as shown in Figure 3. 2. During computation, current computation status and solution variation can be known in real-time via the output menu shown in Figures 5 and 6.

This section will list 3 cases, by way of cases experiment to verify the performance of this model the paper presented on solving the RCPSP. The experiment uses the model to respectively test the 3 cases the research chooses on whether the model is able to obtain a correct solution with high quality, as well as to compare the performance in the results with the solutions obtained from this research or from those from previous researches.

Finally, the sensitivity analysis to the relevant parameters of SA is conducted focusing on the example cases, and a recommended parameter value is proposed with the analyzed result as a basis of setting the parameter for similar cases in the future.

Case of Resource-constrained Scheduling Problem

Three cases were selected respectively from Gen and Cheng (1997) [9], Hegazy (1999) [20], and Erenguc (2003) [19], who used different ways to solve the RCPSP. The ways and the cases will be shown with the detailed description below.

Case Studies.

Case 1: This case derived from Erenguc which is a case which includes 11 activity items and 2 type of resources . The method Erenguc used is the heuristic Minimum Total Slack (MINSLK) says Erenguc's method [19]. While analyzing this case, its assumption and constraint are similar to the original case, therefore, when solving and obtaining its optimal scheduling combination and duration, the maximum usable limitation for each resource R1 and R2 is 4 unit/ day respectively.

Performance analysis:

The total duration of Case 1 to be solved and obtained by using the Critical Path Method (CPM) without any resource limitation is 26 days, and the total duration Erenguc's method solved is 42 days on each resource limitation of 4 unit/day for R1 and R2. However, by using the model the research proposed to establish the multiple resource limitation solving combinatorial mode in this research, the total duration took 34 days to solve and obtain, in satisfying all constraint. Therefore, this model the paper presented is proven to be better than the Erenguc's method, which possessed the highest solving efficiency among 8 heuristic types of criterion in common use, as well as obtaining the better solution.

Case 2: This case derived from Gen and Cheng [9] which is a construction project include 27 activities and 3 types of resource and the information of each item for its project such as activity number, activity title, duration, start date, finish date, follow-up activity, resource demand etc. , among which, the activity no. 1 and activity no. 27 are the start node and finish node respectively. The method Gen and Cheng used is the Genetic Algorithm (GA) says Gen and Cheng's method. While analyzing this case, the assumption and constraint are similar to the original case, therefore, when solving and obtaining its optimal scheduling combination and duration, the maximum usable limitation for each resource (resource types of this case are A, B and C) is 10 unit/ day respectively.

Performance analysis:

The total duration of Case 2 to be solved and obtained by using the Critical Path Method (CPM) is 32 days without any resources limitation. Under the condition of A=B=C=10 unit/ day, the starting solution is 38 days for solving and obtaining, by using the Erenguc's method [19]. However, the optimal duration is 35 days for solving and obtaining by applying the Gen and Cheng' method [9]; to apply the algorithm the research proposed to solve the case, the duration is 33 days with the satisfying of the constraint of resource limitation. As a result, it has better solutions than the Erenguc's method and Gen and Cheng' method. .

Case 3: This case derived from Hegazy in 1999 [20] is a hypothetical project which includes 22 activities and 6 types of resource, The information of each item for the project such as activity number, activity title, duration, start date, finish date, follow-up activity, resource demand etc. , among which, the activity no. 1 and activity no. 22 are the start node and finish node respectively. The method Hegazy used is an improved Genetic Algorithm (GA) says Hegazy's method [20].

While analyzing this case, its assumption and constraint are similar to the original case, therefore, when solving and obtaining its optimal scheduling combination and duration, the resource types of this case are R1, R2, R3, R4, R5 and R6, and the maximum usable limitation for each resource type is 7, 10, 10, 16, 18, and 13 unit/ day respectively.

Performance analysis:

The total duration of Case 3 to be solved and obtained by using the Critical Path Method (CPM) is 32 days without any limitations of supply resource, and under the condition of R1=7; R2=10; R3=10; R4=16; R5=18; R6=13 unit/ day, the total duration is 49 days for solving and obtaining by using the starting solution; however, the optimal duration is 44 days to be solved and obtained in accordance, by applying Hegazy's approach (1999) [20]. However, by using the model the research proposed to establish the multiple resource limitation solving combinatorial mode in this research, the total duration is 43 days to solve and obtain by satisfying all constraints, as a result, it has better solutions than Hegazy's approach. .

From the performance analysis of the above mentioned cases, the solution of resource scheduling solved and obtained by using this algorithm which is better than using the other algorithm with the similar purpose, this algorithm is much easier and convenient not only for the computing procedures over previous researches, but also for obtaining optimal solution or near- optimal solution under the condition of properly setting the parameters.

Therefore, this research mode obviously is the better solving performance.

In addition, whether appropriate application of the SA on setting the parameter during the solving process is also a key factor which influences the solution quality, as a result, the parameter setting method of this proposed model will be further illustrated in the next section of this research.

Setup of Algorithm's Parameter

Firstly, Simulated Annealing (SA) uses the initial temperature as the default status to start searching the optimal solution, where the temperature decreasing rate controls the convergent condition of solving solution in order to reach the final temperature with finishing of the algorithm. Therefore, this section mainly illustrates the setting method of the SA's parameter in this research, where there're 4 key parameters in the SA respectively: initial temperature (T_0), temperature decreasing rate (α), Markov Chain Length (*L*) and final temperature (*Te*); the parameter setting method is the important key in influencing the solving quality, and the following will be illustrate the parameter setting method using Case 3 as the example.

In terms of the initial temperature, due to this research adopting the MINSLK criterion as the starting solution, which is known in previous description, the solution generated from this criterion actually possessed slight convergent tendency. Furthermore, within the computation process of this model, the optimal solution of each temperature in each temperature decreasing procedure is retained as the starting solution for the next temperature value; therefore, the solving solution shall finally reached the convergence. As a result, it is not necessary to set a higher value of the initial temperature value of this mode for the actual testing; the initial temperature can approximately be between 2. 5 and 9. 5 in obtaining the optimal solution.

As for the Markov Chain Length, Kirkpatrick et al. (1983) [18] recommended the using of its length as the multiple number of decision variables, however, this research adopted a better starting solution, where the characteristic and activity of construction project have stronger relationship of pre/ postposition and the limitation in supplying resources, resulting in the move space of searching solution also decreasing relatively; while setting the Markov Chain Length in accordance with abovementioned characteristic, if the set value is too big, then it will only decrease the solving efficiency. This research set the Markov Chain Length as 2n of problem variables, which indicates that searching 2x6=12 times will be enough for each decrease in temperature.

In terms of the temperature decreasing function, when the research used 10 as the initial temperature to observe the temperature change as with Table 1, from this table we found out that the temperature decreasing function only needs to be set in 0. 85 to satisfy the demand of decreasing temperature at least once. In addition, multiply the Markov Chain Length together to obtain the number of searching times from the initial to the final temperatures, which it is adequate within the case testing, and will not miss the opportunity of finding the optimal solution due to rapid decrease in temperature.

Regarding the final temperature, from the test results of Case 3, it can be discovered that within the generating procedure of the starting solution to the optimal solution, the generated energy difference (difference of days) will be no more than 6 days, so this model is used $\Delta E = 6$, $\Delta E = 10$ and $\Delta E = 1$ to conduct the observation on the changes of final temperature, as shown in Table 2 and Figure 7, which discover that the acceptance probability tends towards to 0 when the final temperature is equal to 0. 5 and indicating that it almost cannot be accepted with any other solution, however, this research adopted the final temperature equal to 0. 05, mainly testing for its condition of equilibrium.

By way of the abovementioned setting method of parameter, this research has arranged the recommended value of setting parameter for these cases as shown in Table 3.

Conclusion

The main objective of this research is to establish an improved SA based model for solving the RCPSP, through comparison of solutions with the model from previous researches. Above all, this paper conducted at the following conclusions:

1. The relevant researches of the SA have already been extensively applied on solving various problems of combinatorial-optimization in other domains with certain achievement, however, it is much more rare for applying on the RCPSP of the construction project than the other algorithms such as mathematic model or GA, etc. , therefore, this research applied the SA on establishing the solving algorithm of RCPSP for the construction project. In addition, based on the result of the performance analysis, the proposed model proved will practically obtain a reasonable, high quality of solution in solving the RCPSP, as well as obtaining the optimal solution or near-optimal solution.
2. Simple SA selects the starting feasible solution randomly. The proposed model improves the simple SA algorithm using MINSLK to obtain the feasible starting solution. MINSLK have been proved that have higher efficiency on searching good solution than other heuristic rules. Therefore, compared with the other models (such as: mathematical model, conventional heuristic model (series method, parallel method, etc.), AI based computational model, etc) to solve the RCPSP, some complicated procedures are used to determine the resource priority allocation sequence, the steps for searching solutions in the proposed model can be remarkably reduced. Also, based on the result of performance test with the other model, the proposed model provides a better solution quality than that of the other algorithms as well as the method of using keeping the optimal solution for each temperature while

Table 1. Temperature Decreasing Status when Initial Temperature is 10

Number of Temperature Decreasing Times	Temperature Decreasing Function = 0.85	Temperature Decreasing Function = 0.90	Temperature Decreasing Function = 0.95
1	8.075	8.55	9.025
2	6.86375	7.695	8.57375
3	5.8341875	6.9255	8.1450625
4	4.959059375	6.23295	7.737809375
5	4.215200469	5.609655	7.350918906
6	3.582920398	5.0486895	6.983372961
7	3.045482339	4.54382055	6.634204313
8	2.588659988	4.089438495	6.302494097
9	2.20036099	3.680494646	5.987369392
10	1.870306841	3.312445181	5.688000923
11	1.589760815	2.981200663	5.403600877
12	1.351296693	2.683080597	5.133420833
13	1.148602189	2.414772537	4.876749791
14	0.976311861	2.173295283	4.632912302
15	0.829865081	1.955965755	4.401266687
16	0.705385319	1.760369179	4.181203352
17	0.599577521	1.584332261	3.972143185
18	0.509640893	1.425899035	3.773536025
19	0.433194759	1.283309132	3.584859224
20	0.368215545	1.154978219	3.405616263
21	0.312983214	1.039480397	3.23533545
22	0.266035731	0.935532357	3.073568677
23	0.226130372	0.841979121	2.919890243
24	0.192210816	0.757781209	2.773895731
25	0.163379194	0.682003088	2.635200945
26	0.138872315	0.613802779	2.503440897
27	0.118041467	0.552422502	2.378268853
28	0.100335247	0.497180251	2.25935541
29	0.08528496	0.447462226	2.146387639
30	0.072492216	0.402716004	2.039068257
31	0.061618384	0.362444403	1.937114845
32	0.052375626	0.326199963	1.840259102
33	0.044519282	0.293579967	1.748246147

Table 2. Variation Condition of Final Temperature

Temp.	Acceptable Probability of ΔE=10	Acceptable Probability of ΔE=6	Acceptable Probability of ΔE=1
0.0005	0	0	0
0.005	0	0	1.3839E-87
0.05	1.3839E-87	7.66765E-53	2.06115E-09
0.5	2.06115E-09	6.14421E-06	0.135335283
1	4.53999E-05	0.002478752	0.367879441
2	0.006737947	0.049787068	0.60653066
3	0.035673993	0.135335283	0.716531311
4	0.082084999	0.22313016	0.778800783
5	0.135335283	0.301194212	0.818730753
6	0.188875603	0.367879441	0.846481725
7	0.239651036	0.424372846	0.8668779
8	0.286504797	0.472366553	0.882496903
9	0.329192988	0.513417119	0.894839317
9.5	0.349018071	0.53175153	0.900087626
10	0.367879441	0.548811636	0.904837418
20	0.60653066	0.740818221	0.951229425
30	0.716531311	0.818730753	0.9672161
40	0.778800783	0.860707976	0.975309912
50	0.818730753	0.886920437	0.980198673
60	0.846481725	0.904837418	0.983471454
70	0.8668779	0.917856438	0.985815842
80	0.882496903	0.927743486	0.9875778
90	0.894839317	0.935506985	0.988950389
100	0.904837418	0.941764534	0.990049834
200	0.951229425	0.970445534	0.995012479
500	0.980198673	0.988071713	0.998001999
1000	0.990049834	0.994017964	0.9990005

Table 3. Recommended Value of Parameter Setting of this Research

Type of Parameter	Recommended Value
Initial Temperature（T_0）	**10**
Temperature Decreasing Rate（α）	**0.85**
Markov Chain Length（L）	**12**
Final Temperature（Te）	**0.05**

3. replacing different temperatures that will not only decrease the initial temperature with the shorter time on solution searching, but also ensure the proposed model can be gradually convergent to the optimal solution and obtain a better solving quality than the other models from previous researches.

The model proposed provides not only excellent performance in solving the RCPSP but also a good user interface compared with existing software systems. The model has been executed in Visual Basic 6. 0 program, linked with Microsoft Project 2000. The model proposed presents is one of great efficiency and help for the practitioner in the real world.

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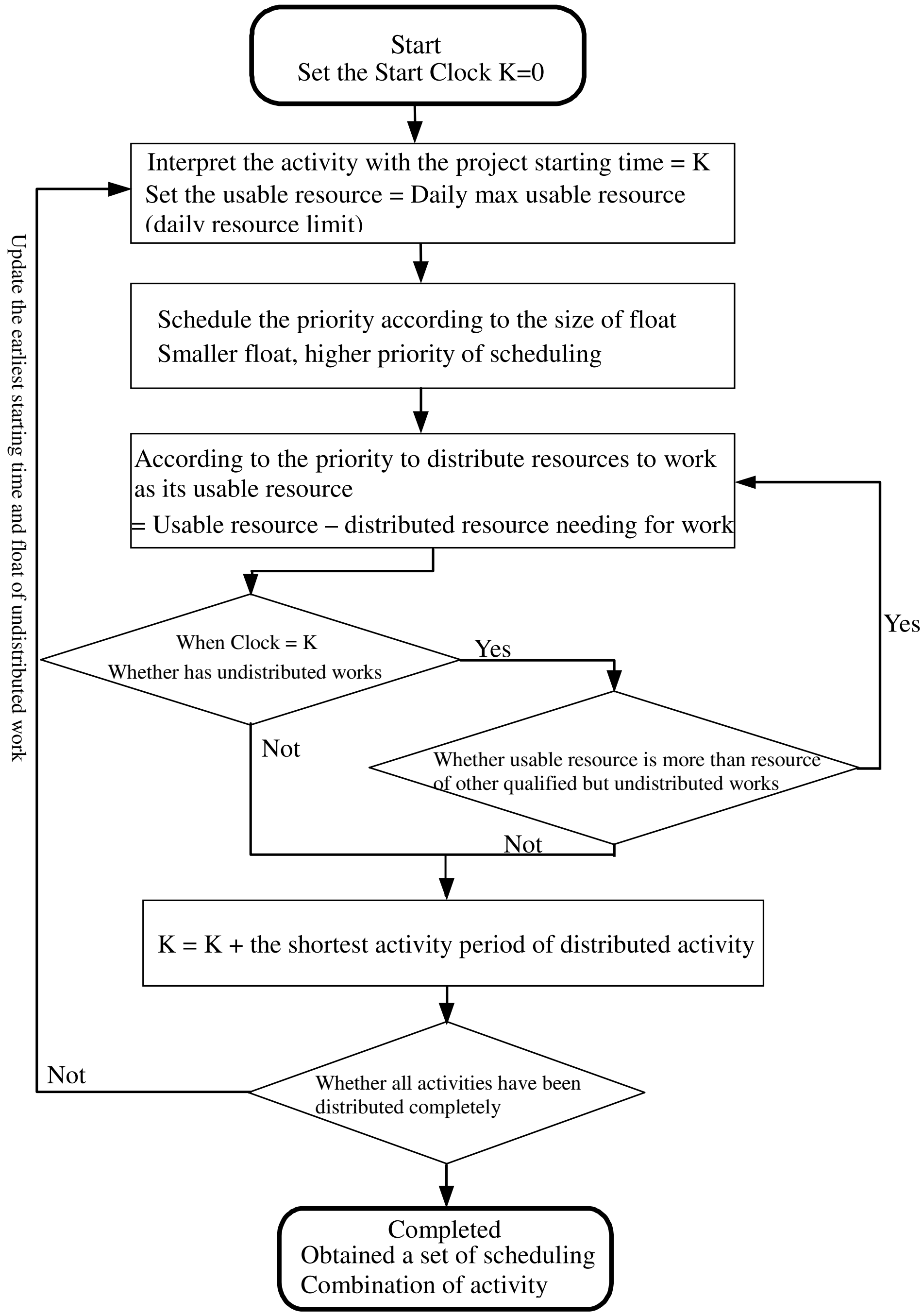

Figure 1. Starting Solution Flowchart of MINSLK

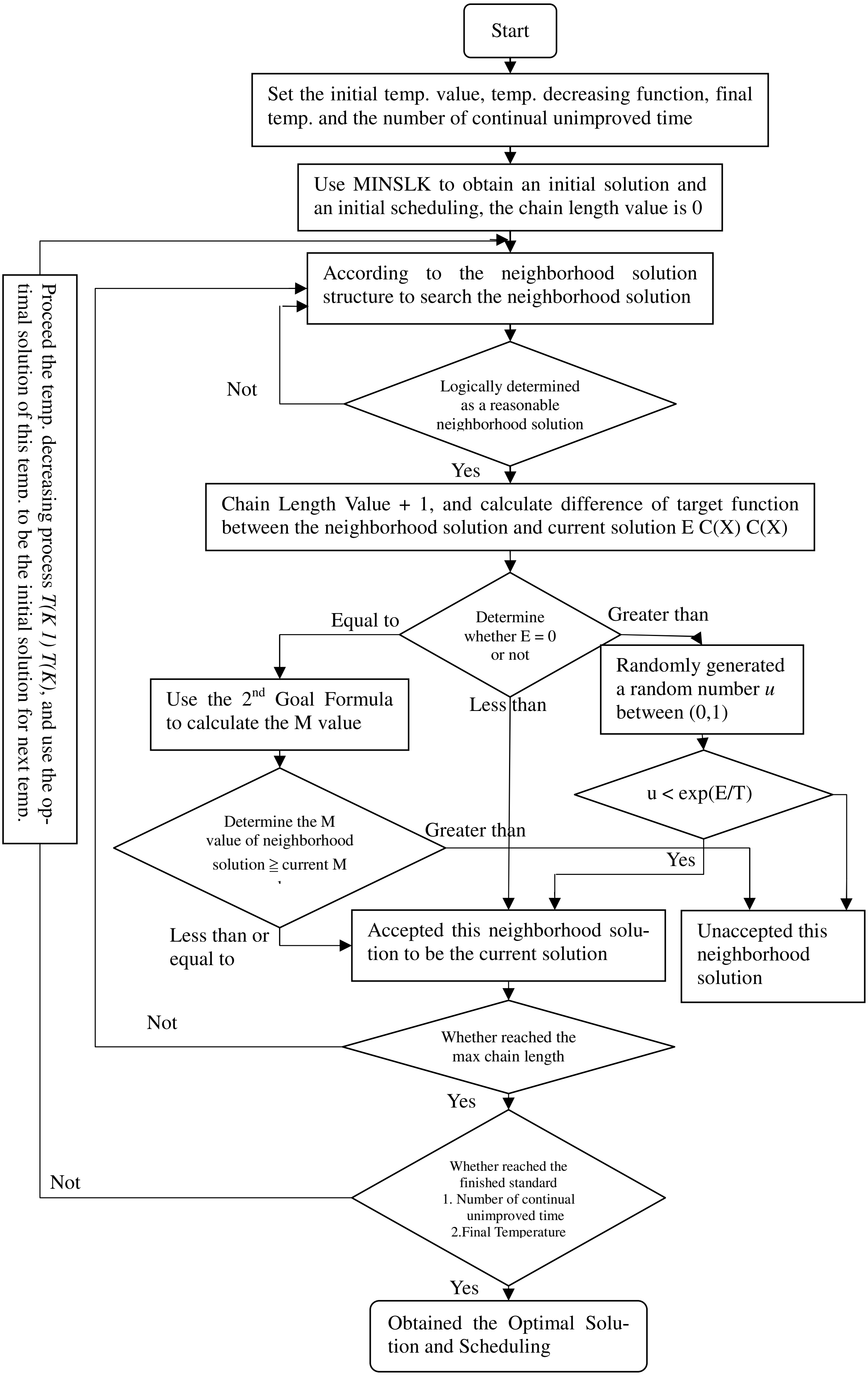

Figure 2. Algorithm of RCPSP using improved SA

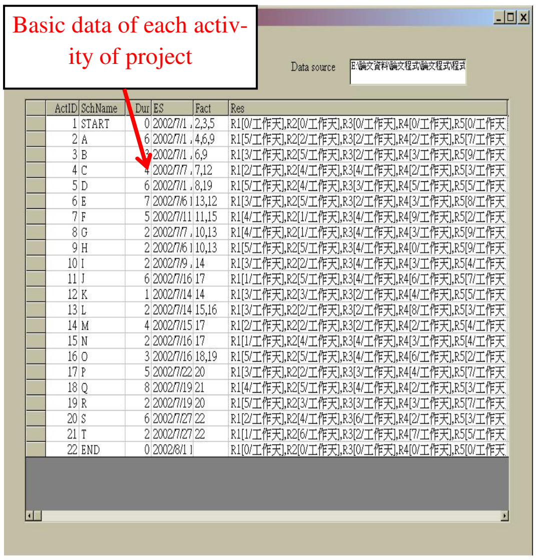

Figure 3. Program menu 1, which shows the data of the sample project

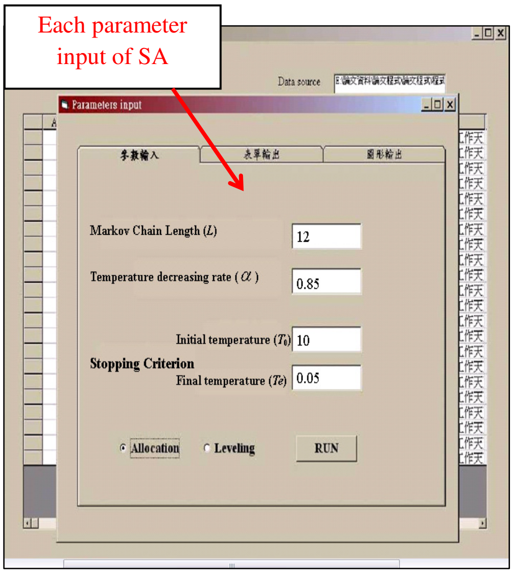

Figure 4. Program menu 2, which let the user set the parameters of the program

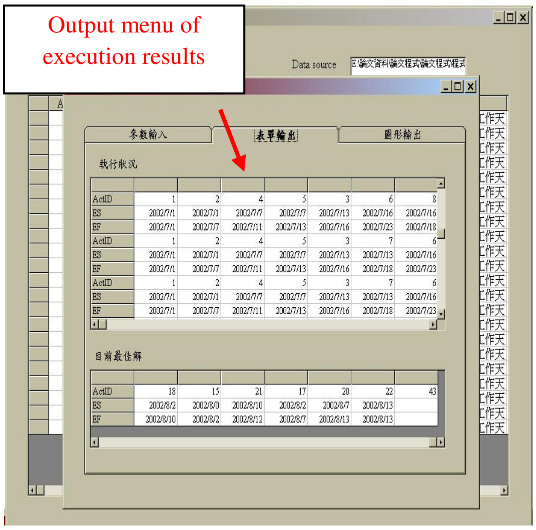

Figure 5. Program menu 3, which shows the results of the computation using the algorithm using the paper's algorithm

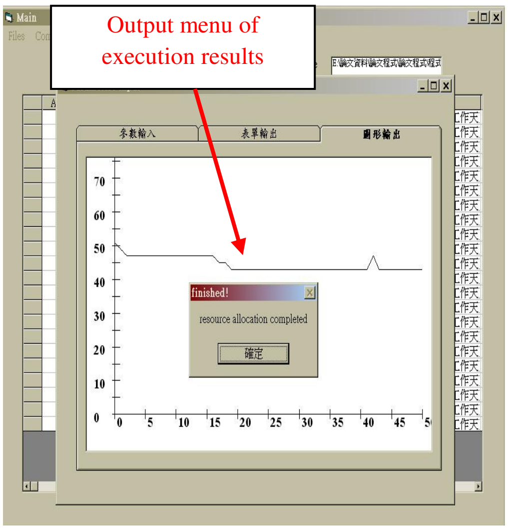

Figure 6. Program menu 4, which shows the results of the computation using the algorithm using the paper's algorithm

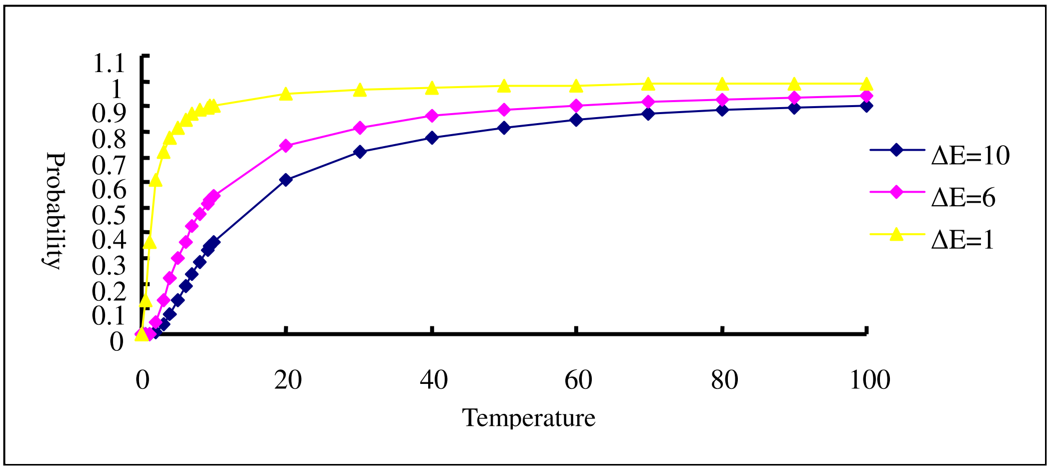

Figure 7. Final Temperature Variation Diagram