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Resource-constrained Scheduling at Different Project Sizes

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Abstract: The resource constrained scheduling problem (RCSP) constitutes one of the most challenging problems in Project Management, as it combines multiple parameters, contradicting objectives (project completion within certain deadlines, resource allocation within resource availability margins and with reduced fluctuations), strict constraints (precedence constraints between activities), while its complexity grows with the increase in the number of activities being executed. Due to the large solution space size, this work investigates the application of Genetic Algorithms to approximate the optimal resource alolocation and obtain optimal trade-offs between different project goals. This analysis uses the cost of exceeding the daily resource availability, the cost from the day-by-day resource movement in and out of the site and the cost for using resources day-by-day, to form the objective cost function. The model is applied in different case studies: 1 project consisting of 10 activities, 4 repetitive projects consisting of 40 activities in total and 16 repetitive projects consisting of 160 activities in total, in order to evaluate the effectiveness of the algorithm in different-size solution spaces and under alternative optimization criteria by examining the quality of the solution and the required computational time. The case studies 2 & 3 have been developed by building upon the recurrence of the unit/sub-project (10 activities), meaning that the initial problem is multiplied four and sixteen times respectively. The evaluation results indicate that the proposed model can efficiently provide reliable solutions with respect to the individual goals assigned in every case study regardless of the project scale.

Key words: Resource constrained scheduling, Resource leveling, Genetic algorithms, Multi objective optimization

1. INTRODUCTION

The resource-constrained scheduling problem (RCSP) is one of the most investigated problems during the past decades, however, it still holds the unabated interest of the scientific community due to its significance in Project Management. The RCSP has become a standard problem in the context of project scheduling, whose aim is to schedule activities optimally with regard to time and resource levelling, while taking into consideration precedence constraints and project completion deadlines.

The numerous extensios of the RCSP problem [1] and its applications have attracted researchers to develop a variety of methods and algorithms for addressing this problem. Such approaches can be categorized into two main classes: exact methods and stochastic methods (heuristic and metaheuristic methods or evolutionary algorithms). Exact methods, such as linear/integer programming, focus on establishing mathematical relationships to describe project goals and constraints in a linear form that will be then optimized. Indicative research efforts using linear programming optimization techniques are these of Damay et al. [2], Chakrabortty et al. [3] and Nieves et al. [4]. Even though these methods provide exact solutions their efficiency decreases, mainly with regards to the computational time, as the project size and parameters increase.

For that reason, in the case of NP-hard problems, such as the RCSP problem, research efforts have been directed to stochastic optimization methods and more specifically in metaheuristics, which can basically approximate a near optimal solution using limited computation time [5]. Genetic Algorithms hold the prime interest of the scientific community for exploring near optimum results in resource-constrained scheduling problems. In this class of methods, the works of Kaiafa & Chassiakos [6], Mathew et al. [7], Yassine et al [8] and Samuel & Mathew [9] could be mentioned. Other studies have used hybrid GA schemes or GA based combinatorial methods in order to obtain better solutions. Indicatevily, Kyriklidis et al. [10] combined Ant Colony optimization and Genetic Algorithms to level the daily usage of resources, while Eid et al. [11] utilized Genetic Algorithms and Pareto Front sorting for scheduling linear infrastructure projects.

Many existing studies investigating the resource constrained scheduling problem are typically focusing on small size construction problems, while they are confining their analysis by focusing on a single criterion to evaluate the effectiveness of the produced resource allocation. Concerning the aforementioned research studies four of them focus on projects consisting of up to 20 activities, two of them develop project networks with the number of activities ranging from 60 to 84 while other works examine at the same time different project scales. More specifically, Mathew et al. [7] study two different repetitive projects with 20 and 90 activities respectively as well as Eid et al. [11] that work on similar size projects (20 and 75 activities respectively).

This study attempts to analyse the effect of the project size on the effectiveness of allocating project resources by developing 3 case studies examining projects with 10, 40 and 160 activities respectively. The development of the optimization model employs three alternative decision parameters with practical value.

2. PROPOSED MODEL

The objective function of the proposed model represents the total cost to be minimized and is formulated as the cost summation of all optimization sub-objectives. The sub-objectives are the project completion goal within a deadline (or as soon as possible), the confinement of the daily resource usage within the availability level, and the development of a flat daily resource usage pattern throughout project execution [12]. In the present work, a number of parameters that can be more tangibly connected to the real effect of resource imbalance or constraint exceedance are assessed in terms of their competence to capture the various deficits of non-optimal resource allocation.

- The cumulative number of resources exceeding the daily resource availability, which represents the financial impact of recruiting additional resources than initially planned (Resource Limit Exceedance - RLE).
- The square of the sum of resources daily consumption, which represent the cost for using resources (human and machinery) at the construction site day by day (R^2).
- The sum of resource unit deviations from day to day, which represents the cost for moving resources (human and machinery) in and out of the construction site day by day (Resources In and Out-RIO).

The above decision criteria are composing an objective function of the following form:

$$C= w_1*RLE+w_2*RIO+w_3*R^2 \tag{1}$$

wi the corresponding unit cost values, defined by the user and representing the problem characteristics. In this way, the criteria can be evaluated either individually or collectively.

This analysis considers a single resource type as well as a predefined duration and daily resource usage for each activity. The optimization is performed by rescheduling activities according to their precedence relationships and time slacks.

The proposed model has been implemented in an Ms-Excel spreadsheet and the optimization is performed via a commercial optimization software (Palisade Evolver 8.1) which works as an Excel add-in. The Genetic Algorithm that has been employed to search for optimal solutions uses 50 chromosomes to form the initial population with crossover and mutation rate 0.5 and 0.1 respectively. An iterative procedure of 200,000 trials or 60 minutes of runtime is used for all the scenarios that have been tested.

3. RESULTS

Three different case studies have been considered in this analysis to illustrate the algorithm application. The first case sudy examines a simple project (basic unit) consisting of 10 activities whose durations, precedence relations, and resource requirements are shown in Table 1. Case Study 2 builds upon the recurrence of the subproject presented in Case study 1 and forms a project of 4 repetitive basic units (two serial and two parallel executions of the subproject) consisting of 40 activities in total. The same principle applies to the formulation of Case Study 3, which is created by the repetition of 16 basic units (four serial and four parallel executions of the subproject) comprising of 160 activities in total. The usage of a simple project's repetition is chosen in order to increase the scalability potential of the case study and to enable the efficient resource allocation potential assessment. Figure 1 presents the network diagram of the basic unit/sub-project and Figure 2 the resource histograms for the early project schedule of each Case Study. The normal durations for Case Study 1, 2 and 3 are 17, 34 and 68 days respectively.

Table 4. Project data for the basic unit

Activity	Predecessors	Duration	Resources
A	Start	5	2
B	Start	10	2
C	Start	4	2
D	A	7	2
E	C	5	2
F	A	4	2
G	E,D,B	3	2
H	C	6	2
I	Start	4	2
J	F,G,H,I	2	2

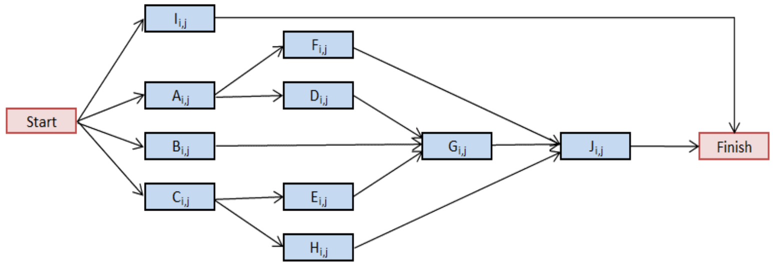

Figure 13. Network diagram of the basic unit (sub-project)

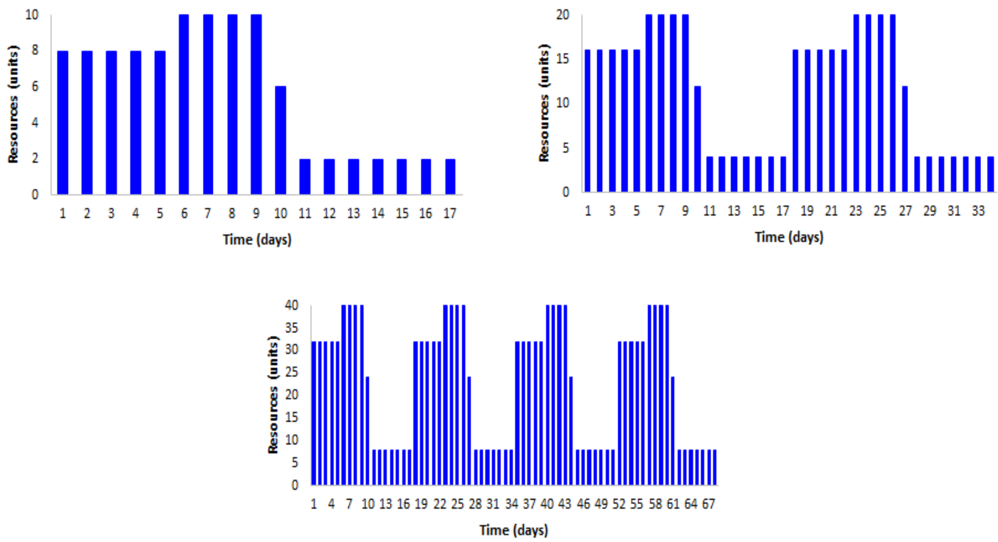

Figure 14. Resource histograms for the early starts of the application projects schedule.

In this analysis several scenarios have been tested using three alternative optimization criteria as indicated in Table 2. Table 2 provides the optimal results of the three case studies considering i) the minimization of the cost of exceeding the daily resource availability, ii) the minimization of the cost of the daily resource usage and iii) the minimization of the cost for moving resources in and out of the project along its duration. The numbers in bold indicate the best criterion value found in each examined level of resource availability or project duration.The numbers in italics provide the initial value of each variable before the optimization process. The results presented in Table 2 indicate that the optimization achieves greater improvements in the minimization of the resource demands rather than in the minimazion of the daily resource movement in and out of the construction site. More specifically, the resource limit exceedance shows a considerable decrease from 60% to 90% depending on the project duration and size, while the resources in and out movement presents a decrease from 9% to 58% respectively.

Table 5. Optimal results for the application case studies

Optimization criteria					
	Before Optimization	Resource limit	Resource usage (R^2)	Resources in and out	Average percentage

		exceedance (RLE)		(RIO)	improvement (%)
Case Study 1: Resource constraint 6 - Project duration 17					
Project duration	*17*	17	17	17	-
Resource limit exceedance (RLE)	*26*	**2**	**2**	18	84%
Resources in and out (RIO)	*20*	16	16	**8**	33%
Case Study 1: Resource constraint 4 - Project duration 25					
Project duration	*17*	25	25	25	-
Resource limit exceedance (RLE)	*46*	**4**	**4**	8	88%
Resources in and out (RIO)	*20*	**10**	**10**	**10**	50%
Case Study 2: Resource constraint 12 - Project duration 34					
Project duration	*34*	34	34	34	-
Resource limitexceedance (RLE)	*104*	20	**16**	58	70%
Resources in and out (RIO)	*72*	64	52	**48**	24%
Case Study 2: Resource constraint 8 - Project duration 50					
Project duration	*34*	50	50	50	-
Resource limitexceedance (RLE)	*184*	**6**	8	40	90%
Resources in and out (RIO)	*72*	36	30	**24**	58%
Case Study 3: Resource constraint 24 - Project duration 68					
Project duration	*68*	68	68	68	-
Resource limit exceedance (RLE)	*435*	**106**	108	310	60%
Resources in and out (RIO)	*272*	244	224	**204**	9%
Case Study 3: Resource constraint 16 - Project duration 100					
Project duration	*68*	100	100	100	-
Resource limitexceedance (RLE)	*736*	78	**54**	174	86%
Resources in and out (RIO)	*272*	156	130	**86**	54%

The resource allocation histograms attributed to the previously stated optimal results are depicted in Figures 3-5 in order to better apprehend the quality of the acquired solution. The resource allocation histograms corresponding to the initial solution of the scenarios under examination present significant peaks in resource demand and large fluctuation in resource usage throughout the project duration (Figure 2). This indicates that the initial solution may not be obtainable in the real world or too expensive to procure. It can bee seen that the criteria RLE, R^2 and RIO provide substantially leveled up histograms as they allocate resources within the project life cycle. Both criteria RLE and R^2 are focusing in keeping the resource allocation close to the resource availability threshold and therefore succeed in having low fluctuations, in number and extent throughout the project. On the other hand, RIO criterion develops highly fluctuating histograms in which however the number of resources in and out is significantly lower in relation to the other criteria.

It is observed that the size of the project that is tested in each Case Study plays a major role in the quality of the solution independently from the optimization criterion that has been chosen. This is due to the fact that as the solution space size increases, it becomes more difficult for the Genetic Algorithm to find the chromosome that approximates better the global optimum. This is depicted in Figures 3-5, where the much more leveled up histograms of Case Study 1 become more rough, with peaks and fluctuations in Case Study 2 and keep deteriorating in Case Study 3.

Furthermore, it should be mentioned that the chosen duration of the project co-shapes the optimization output. For the project deadlines set in 17, 34 and 68 days (corresponding to Case Studies 1, 2 and 3) the resource histograms show a lessen leveling capability compared with the ones developed for project durations of 25, 50 and 100 days respectively. The strict limitations in the first set of project durations do not allow the Genetic algorithm to move freely the activities within the project, whereas in the second set the broader time frames enable the model to find a sequence in the starting dates of the activities that can better approach the fully levelled diagram.

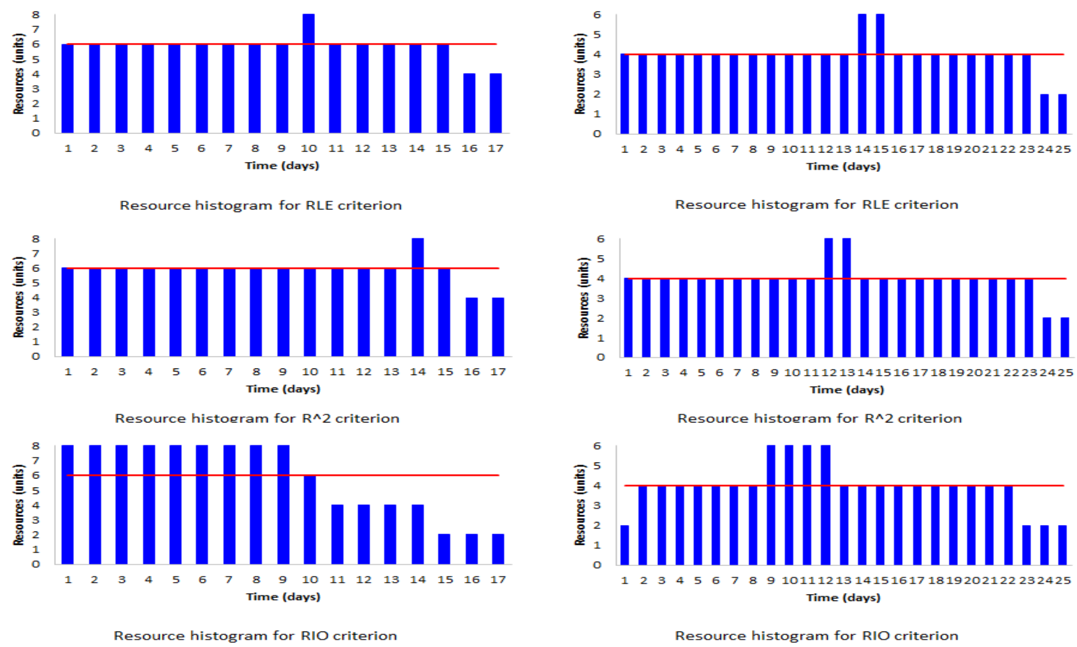

Figure 15. Resource histograms for Case Study 1.

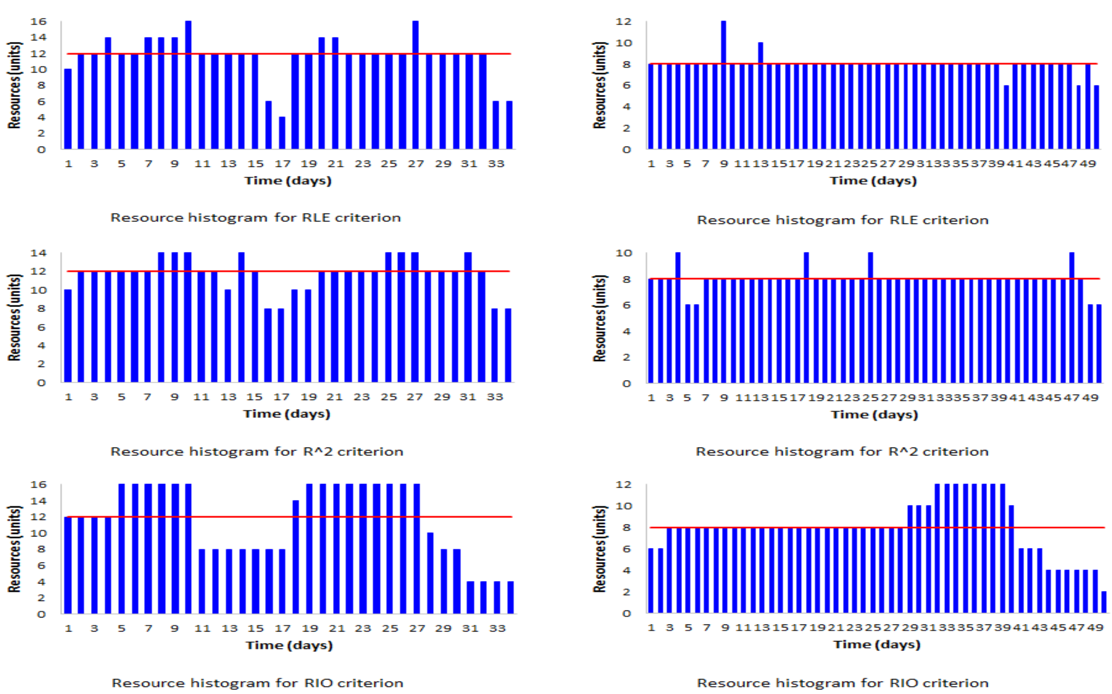

Figure 16. Resource histograms for Case Study 2.

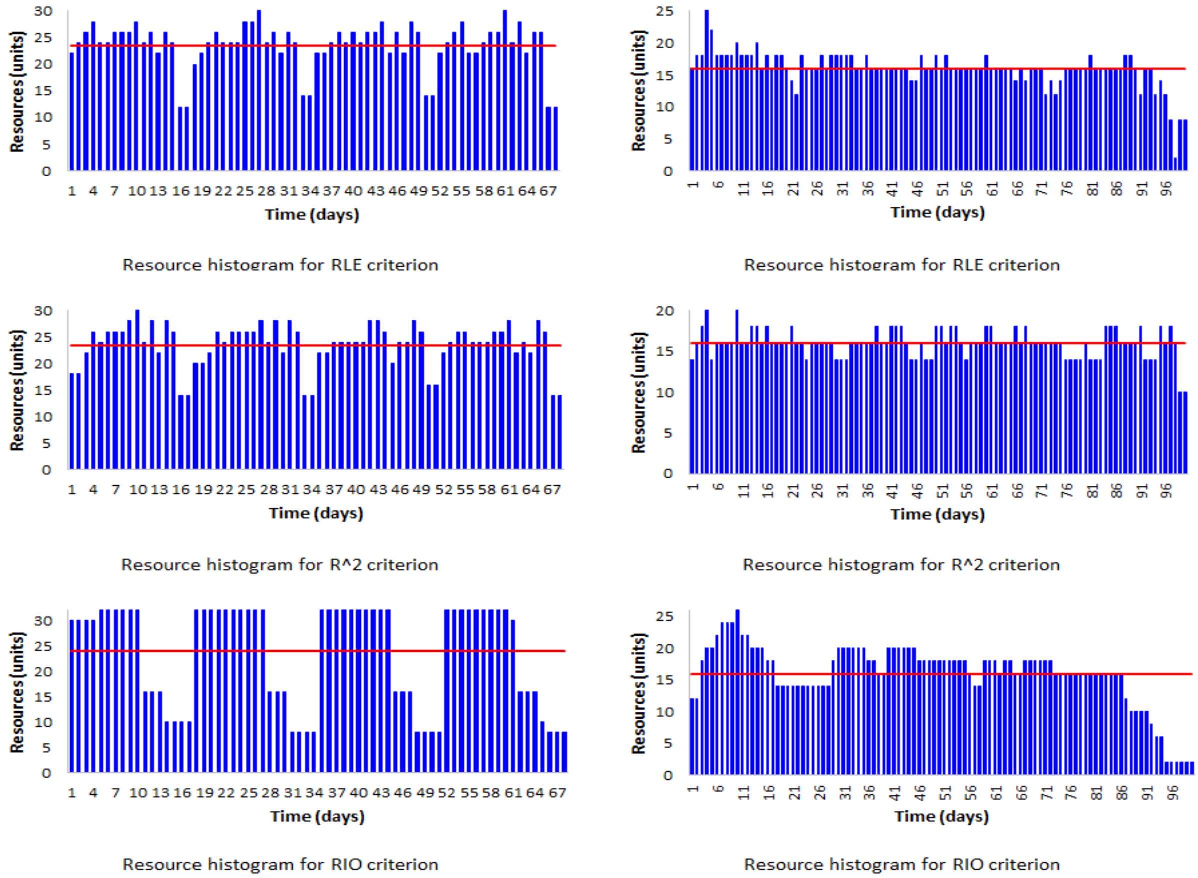

Figure 17. Resource histograms for Case Study 3.

4. CONCLUSIONS

The resource-constrained problem attains the interest of the scientific community for several decades now, as it is one of the most challenging problems in the field of project management. This derives from the fact that it is an optimization problem which integrates multiple and conflicting objective and constraints (e.g. resource allocation without exceeding availability margins, project completion within predefined deadlines, precedence relation between activities). Additionally, the problem's solution space size and therefore its complexity grows significantly as the number of activities increases. Hence, the employment of metaheuristics (Genetic Algorithms) is qualified for approximating the optimal solution.

This analysis develops an optimization model whose aim is to minimize a cost function that integrates costs associated with i) resource availability exceedance ii) daily resource usage and iii) day-by-day resource fluctuations. The present work examines different project sizes and alternative decision criteria to evaluate whether the proposed optimization structures can facilitate the objectives set in actual projects. The optimization is performed with the utilization of Genetic Algorithms as an effective tool to handle large combinatorial problems. The evaluation results indicate that the proposed model can efficiently provide reliable solutions with regards to the individual goals assigned in every project case.

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