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Recent Developments of Computational Intelligence for Resource Constrained Project Scheduling Problems: A Taxonomy and Review

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Abstract— This article presents a broad overview of applications of Computational Intelligence (CI) paradigms in resource constrained project scheduling problems (RCPSP) including Fuzzy system (FS), Artificial Neural Networks (ANN), Particle Swarm Optimization (PSO), Tabu Search (TS), Genetic Algorithms (GA), Simulated Annealing (SA) and other metaheuristics techniques. Recent developments of computational intelligence techniques and its implementations to project scheduling problems are reviewed. Various types of RCPSP and its extensions as a single objective and multiobjective models are introduced. Applications of CI techniques to RCPSP are classified and analyzed on various dimensional including CI paradigms, publication years and numbers, type of RCPSP models as single objective optimization model and multiobjective model as well as RCPSP with renewable, nonrenewable, partially renewable resource constrained. In addition to, a discussion of how these CI paradigms could be applied to solve RCPSP problems and how RCPSP could be analyzed, processed, and optimized using CI paradigms. Challenges and promising research directions in the field of CI and RCPSP are addressed.

Keywords— Resource constrained project scheduling, Multimode, Combinatorial Optimization, Computational intelligence, Hybrid Computational Intelligence.

I. INTRODUCTION

Recently, project management and scheduling became one of the most important directions in both research and practice of operations management, or, more generally, in operational research. Project scheduling, as a part of project management, deals with the allocation of scarce resources to a set of activities that are usually directed toward some major output and require a significant period of time to perform. Project scheduling algorithms could be applied in many applications such as sports scheduling [1], airline scheduling [2] and personnel scheduling [3]. Scheduling problems have long been tackled by CI algorithms as the scheduling problem in its various forms is NP-complete problem see [4] and [5].

The resource constrained project scheduling problem (RCPSP) aims to schedule the activities such that precedence and resource constraints are satisfied while optimizing some managerial objective, e.g. minimizing the project makespan. RCPSP is of great practical importance because its general model can be used for applications in product development, production planning, and a wide variety of construction planning and scheduling applications especially in make-to-order and small batch production such as construction engineering, software development, ships and planes etc. For this reason, the RCPSP has received the attention of many researchers.

Many optimization methods have been proposed for the problem, including implicit enumeration methods, zero-one programming, dynamic programming, and etc see e.g. [6], [7]. However, the RCPSP problem is known to be strongly NP-hard [8], it is no surprise that the majority of current algorithms are computational intelligence. The RCPSP has various features as single mode, multi-mode, with non preemptive or preemptive resources, renewable or non-renewable resources. This problem was been widely studied in the single objective case, however, the multiobjective version of the RCPSP is scant. Comprehensive reviews of the state-of-the-art of the RCPSP could be found in the literature, the most recent one are provided in Hartmann and Briskorn [9].

It is not a surprise that one of the key founding disciplines of computational intelligence is related to the sources of intelligence in nature, i.e. biology. Bio-inspired computing uses methods, mechanisms, and features from biology to develop novel computer systems for solving complex problems. The motivation of bio-inspired computing is discovering new techniques with competitive advantage over the traditional approaches for a given class of problems. In the case of computational intelligence, biologically motivated computing has driven the development of three methods - neural networks, evolutionary computation, and swarm intelligence from their biological metaphors, respectively, brain functioning, evolutionary biology, and social interaction.

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To provide useful insights for CI applications in RCPSP, we structure the rest of this paper as follows. In Section II we remind the overview of the standard RCPSP which will be the basis for further generalizations, besides we will give a brief description about its extensions and variations. The mathematical formulations of RCPSP will be presented in section III. Section IV introduces some fundamental aspects and key components of modern computational intelligence including Artificial Neural Networks (ANN), Tabu Search (TS), Fuzzy Sets (FS), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Genetic Algorithms (GA). A review of the current literature on CI-based approaches in project scheduling with resource constraints is provided in Section V. Section VI discusses some successful work to illustrate how Hybrid CI could be applied to different RCPSP problems. A general discussion and limitations of using CI in project scheduling will be given in section VII. Conclusions, Challenges, and Future Directions are addressed in Section VIII.

II. PROBLEM DESCRIPTION

Project scheduling is an important task in project management. The presence of scarce resources as well as precedence relations between activities makes project scheduling a difficult task. During the last decades, the RCPSP has become a standard problem for project scheduling in the literature. The RCPSP is strongly NP-hard [8]. Analyses of the problem resulted in the development of exact as well as heuristic algorithms. Therefore, many researchers have developed more general project scheduling problems, often using the standard RCPSP as a starting point. Several survey papers on project scheduling have been published, many papers focus on methods for the RCPSP for example [10], [11] and a few common variants [12], [13].

The RCPSP can be characterized by the objective function, features of resources, and preemption conditions. Minimization of project duration is often used as an objective of the RCPSP, while other objectives such as minimization of the total project cost and leveling of resource usage are also considered. Resources involved in a construction project can be renewable (i.e., recoverable after serving an activity, such as equipment or crew) or nonrenewable (i.e., limited in amount over project process and not recoverable, such as cement or sand). Preemption means that some activities (e.g., frame-installing) can be interrupted, while nonpreemption means that some activities (e.g., concreting) are not allowed to be interrupted once in progress [14].

In practice, the activity could be accomplished by alternative modes. Each mode reflects a unique, feasible alternative, which combines a duration, and resource requirement that allows for accomplishing the underlying activity in various ways. The multi-mode problem (MRCPSP) is a generalized version of the standard problem (RCPSP), where each activity can be executed in one of several modes representing a relation between resource requirements of the activity and its duration. The schedule has to be precedence- and resource-feasible and no activity may be interrupted. The resources can be renewable, non-renewable, doubly constrained, and/or partially renewable, where the renewable resources are limited period-by-period, the non-renewable resources are limited for the entire project, the doubly constrained ones are limited both for each period and for the entire project, and the availability of the partially renewable resources is defined for a specific time interval (a subset of periods). However, under discrete resources, the doubly constrained resources need not be taken into account explicitly since they can be incorporated by properly enlarging the sets of the first two types of resources. The objective is to find an assignment of modes to activities as well as precedence- and resource-feasible starting times of all activities such that the makespan of the project is minimized. Moreover, for more than one non-renewable resource the problem of finding a feasible solution of the MRCPSP is already NP-complete [15].

Financial aspects of the problem appear when, generally, a series of cash flows (positive and/or negative) occur over the course of the project. Positive cash flows (i.e. cash inflows) correspond to payments for the execution of activities. Negative cash flows (i.e. cash outflows) include expenditures for labor, equipment, materials, etc. Time value of money is taken into account by discounting the cash flows. The most commonly considered financial objective is the maximization of the net present value (NPV) of all cash flows of the project. The resulting problem is then called the multimode resource-constrained project scheduling problem with discounted cash flows (MRCPSPDCF) [16]. Project scheduling is an inherently multi-objective problem, since managers want to finish projects as soon as possible with the minimum cost and the maximum quality. However, there are only a few papers dealing with multiobjective resource-constrained project scheduling problems (MORCPSP). Moreover, there is no theoretical study in the literature that establishes the fundamentals for correct algorithmic developments. Except in Ballestín and Blanco, [17] who tried to close the gap by proving several results for MORCPSP. With these results as a basis, exact, heuristic and metaheuristic procedures capable of obtaining a set of efficient solutions for several important MORCPSP can be created.

III. MATHEMATICAL FORMULATION

We consider a project which consists of n activities (jobs, tasks). Due to technological requirements precedence relations between some of the activities enforce that an activity j, $j = 2,\dots, n$, may not be started before all its predecessors are finished. The structure of the project is depicted by an activity-on-node (AON) network $G = (V, P)$ where the nodes and arcs represent the activities V and precedence relations P, respectively. Activity 1 is the only start activity and activity n is the only finish activity. The RCPSP may be formulated as an integer programming problem. The $0-1$ decision variable $x_{jt} = 1$ if activity A_j is assigned a completion time at the end of period t; otherwise, $x_{jt} = 0$. Associated with each activity A_j are its earliest finish time EF_j, and latest finish time LF_j, calculated as in Kelley and Walker [18]. The value of LF_n is set equal to the scheduling horizon H, which never exceeds the sum of all activity durations. The following formulation defines the RCPSP [19]:

$$\text{Minimize} \quad \sum_{t=EF_n}^{LF_n} t x_{nt} \qquad (1)$$

Subject to

$$\sum_{t=EF_j}^{LF_j} x_{jt} = 1 \ \text{ for } j = 1,\ldots,n \qquad (2)$$

$$\sum_{t=EF_i}^{LF_i} t x_{it} \le \sum_{t=EF_j}^{LF_j} t x_{jt} - d_j \ \text{ for all } (A_i, A_j) \in P \qquad (3)$$

$$\sum_{j=1}^{n} r_{jk} \sum_{q=\max(t, EF_j)}^{\min(t+d_j-1, LF_j)} x_{jq} \le R_k \ \text{ for } k = 1,\ldots,R; t = 1,\ldots,H \qquad (4)$$

$$x_{jt} \in \{0,1\} \ \text{ for } \ j = 1,\ldots,n; \ \ t = EF_j,\ldots.,LF_j \qquad (5)$$

Constraints (2) ensure that each activity is completed exactly once. The set of all pairs of activities (A_i, A_j) such that A_i directly precedes A_j is denoted by *P*. Hence, precedence constraints are represented by inequalities (3). Constraints (4) guarantee that no more than the available number of units of each resource are required in any time period, and constraints (5) state that we consider binary decision variables. The solution of the problem (1)-(5) defines an optimal schedule as a list of activity completion times. For more formulations for RCPSP see [20]–[23].

In the RCPSP it is assumed that an activity once started, must be continuously processed until completion. In practice, however, it may be the case that the processing of an activity may be interrupted and resumed at a later time. When resource availability is limited, activity preemption may result in shorter project duration. The introduction of activity preemption increases the number of possible solutions and consequently the computational complexity of the RCPSP. The minimum makespan problem with preemption was formulated by Talbot, [24]. Partially renewable resources were first introduced by Böttcher, et al., [25]; they proposed an integer linear formulation.

For the MRCPSP, the most popular 0-1 programming model based on an extension of the formulation by Pritsker, et al., [19] has been presented by Talbot, [24], which is described below. Multi-objective versions of these problems are considered by Słowinski, [26]. For nonpreemptable activities executed in several modes using renewable, nonrenewable, and doubly constrained resources, the first approach was presented by Talbot, [24]. MRCPSP with resource vacations by defining time-varying resource capacities was introduced in Drexl and Grüenewald, [27]. The preemptive MRCPSP with resource vacations and activity splitting was formulated in Buddhakulsomsiri and Kim, [28]. A mathematical formulation for the MRCPSP with generalized precedence constraints and mode-dependent time lags was proposed in Sabzehparvar and Seyed-Hosseini, [29]. In Zapata, etal., [30], three alternative formulations of the multi-project version of the MRCPSP was proposed, in two of them time is a continuous variable. Obviously, under some assumptions these models may be used to formulate mathematically the MRCPSP. MRCPSP with renewable and nonrenewable resources was formulated in Van Peteghem and Vanhoucke, [31].

Let

x_{jmt} is a binary variable equals to 1 if activity A_j executed in mode $m \in M_j$ is complete at the end of time period *t*.

$R_k^{\rho} (R_k^{v})$ is the number of available units of the *k*th (*l*th) renewable (nonrenewable) resource.

r_{jmk}^{ρ} is the number of units of the *k*th renewable resource $(k = 1,\ldots,R)$ required by activity A_j executed in mode $m \in M_j$.

r_{jml}^{v} is the number units of the *l*th nonrenewable resource $(1 = 1,\ldots,N)$ required by activity A_j executed in mode $m \in M_j$.

d_{jm} is the duration of activity A_j executed in mode $m \in M_j$.

EF_j, LF_j are calculated assuming that the shortest duration mode is assigned to each activity, and the planning horizon H is calculated for the modes with the longest durations.

P is the set of all activities pairs (A_i, A_j) such that A_i directly precedes A_j.

The mathematical model of the MRCPSP was formulated as follows [24]:

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$$\text{Minimize} \quad \sum_{m=1}^{|M_n|} \sum_{t=EF_n}^{LF_n} t x_{n,m,t} \tag{6}$$

subject to

$$\sum_{m=1}^{|M_j|} \sum_{t=EF_j}^{LF_j} x_{jmt} = 1 \quad \text{for } j = 1,\ldots,n \tag{7}$$

$$\sum_{m=1}^{|M_j|} \sum_{t=EF_i}^{LF_i} t x_{imt} \le \sum_{m=1}^{|M_j|} \sum_{t=EF_j}^{LF_j} (t - d_{jm}) x_{jmt} \quad \text{for all } (A_i, A_j) \in P \tag{8}$$

$$\sum_{j=1}^{n} \sum_{m=1}^{|M_j|} r_{jmk}^{\rho} \sum_{q=\max\{t,EF_j\}}^{\min\{t+d_{jm}-1,LF_j\}} x_{jmq} \le R_k^{\rho} \quad \text{for } k = 1,\ldots,R;\; t = 1,\ldots,H \tag{9}$$

$$\sum_{j=1}^{n} \sum_{m=1}^{|M_j|} r_{jmt}^{v} \sum_{t=EF_j}^{LF_j} x_{jmt} \le R_l^{v} \quad \text{for } l = 1,\ldots,N \tag{10}$$

$$x_{jmt} \in \{0,1\} \quad \text{for } j = 1,\ldots,n;\; m \in M_j;\; t = EF_j,\ldots,LF_j \tag{11}$$

The objective function (6) minimizes the project duration (makespan) in which x_{nmt} is the finishing time of the end activity with $|M_n|$ modes. Constraints (7) ensure that each nonpreemptable activity is performed exactly once in exactly one mode. Precedence constraints are guaranteed by (8). Constraints (9) and (10) ensure that the renewable and nonrenewable resource limits are not exceeded, respectively. Finally, constraints (11) define the binary status of the decision variables.

There is a general case of MRCPSP in the situations involving minimum and maximum time lags or Generalized Precedence Relations called MRCPSP-GPR in which the duration/cost of an activity is treated as a function of both the resource requirements (mode selection) and the amount of crashing (duration reduction), applied within the selected mode. The mathematical programming formulation for MRCPSP-GPR has been developed by De Reyck and Herroelen, [32] based on the previous work of Talbot, [24]. This complex case has been introduced by Ahn and Erenguc, [33] and called Resource-Constrained Project Scheduling Problem with Multiple Crash able Mode or briefly RCPSPMCM. The problem is strongly NP-hard [34], [35].

Various types of trade-offs occur in project scheduling practice and have been studied in the context of project scheduling. In many real-life projects, it often occurs that only one renewable bottleneck resource is available (e.g. labor) in constant amount throughout the project. The problem that arises in such project scheduling environments is referred to as the discrete time/ resource trade-off problem (DTRTP) [36]. The DTRTP is a subproblem of the multi-mode resource-constrained project scheduling problem (MRCPSP). As a generalization of the RCPSP, the DTRTP is NP-hard. The DTRTP with multiple resource types (MDTRTP) was formulated by Ranjbar, etal. [37].

The discrete time-cost trade-off problem, hereafter referred to as DTCTP, is a well-known problem from the project management literature [38]. Integer programming formulation for the irregular costs project scheduling problem with time/cost trade-offs (PSIC) was presented in Szmerekovsky and Venkateshan, [39]. A multi-mode resource-constrained discrete time/cost tradeoff model (MRC-DTCTP) are just like DTCTP, MRC-DTCTP could be used to find the minimum project cost while meeting a given deadline (the deadline problem) or minimize the project duration meeting a given budget constraint (the budget problem). Also it might be of interest to compute the entire time-cost curve. It was suggested that the quality of a completed project may be affected by project crashing [38]. A formulation with a quality maximizing objective was developed in Icmeli-Tukel and Walter, [40]. In Tiwari, etal., [41], authors modified the formulation of [42] to incorporate efficiency/quality tradeoff with MRCPSP.

A regular objective function is one in which the objective function is never made worse by reducing the completion time of a activity without increasing the completion time of any other activity. A non-regular objective function violates this property. Because of the time dependent nature of these objective function costs, the objective function value can actually increase by reducing the completion time of an activity (all else being equal), and so these are non-regular objective functions such as the resource leveling problem where the main objective is to limit the amount of resource usage variation from period to period, which may be costly in certain contexts see [43] for mathematical formulations.

Another type of non-regular objective function is minimizing renewable resource costs subject to a project due date; this problem is known as resource investment problem (RIP) [44]. This problem is proved to be NP-hard [19]. A mathematical model of the RIP with discounted cash flows (RIPDCF) in which the activities are subject to generalized precedence relations was presented [45]. A project deadline was added to the NPV model; many formulations of the problem were introduced as linear programming formulation [46] and zero-one integer-programming model [47].

Another nonregular measure of performance is the RCPSP with weighted earliness-tardiness costs (RCPSPWET),

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where the objective is to minimize the weighted earliness-tardiness penalty costs of the activities in a project. In this problem, a due date, a unit earliness penalty cost and a unit tardiness penalty cost are assigned to the activities and the objective is to schedule the activities to minimize the weighted penalty cost of the project. This problem often occurs in practice since many project schedulers have to deal with due dates and penalty costs. Costs of earliness include extra storage requirements and idle times and implicitly incur opportunity costs (for mathematical formulations see [48] and [49]).

The deterministic resource-constrained project scheduling problem with discounted cash flows (RCPSPDC) involves the scheduling of the project activities in order to maximize the net present value subject to the precedence and resource constraints [49]. The multi-mode version of the RCPSPDC (MRCPSPDC) has been considered in several articles. A problem with positive and negative cash flows and availability constraints on capital and renewable resources was also discussed [50]. MRCPSPDC with renewable, non-renewable and doubly constrained resources was also presented and formulated [51] and [52].

In multi-resource-constrained project scheduling problems, an activity may require a set of operations, or a set of successive resources. For a given operation, several resources may be in parallel, which means the task can select any one of these resources for processing. An activity might also need to complete processing on one resource before it begins processing on another resource, where successive resources are needed in series. The multi-resource constrained project scheduling problem with multiple modes (mcPSP-mM) with precedence subsumes the activity shop, flow shop, assembly line balancing, and related scheduling problem, the mcPSP-mM consists of a number of activities with known processing time, multiple resources, and multimode. The managerial objective is to minimize the makespan. The multiple resources are renewable and nonrenewable resource constraints. The multiple resources are available in limited quantities but nonrenewable from period to period. Activities are not preemptable; there is only one execution mode for each activity along with precedence constraints of activities. mcPSP-mM is a complex process involving many resource types that require optimum use. Often, the requirement of a type of resource may influence the requirement of other types, mcPSP-mM was mathematically formulated [53].

The Dynamic Resource-Constrained Project Scheduling Problem (DRCPSP) deals with an uncommon kind of resource called Dynamic Resource. Unlike classical project scheduling problems where resources may be renewable or nonrenewable (both with a bounded quantity), the DRCPSP allows an unbounded amount of these resources because they are consumed when a task is executed, but are produced by tasks after their activations. For a mathematical formulation for DRCPSP see [54] and [55].

The resource constrained multi-project scheduling problem (RCMPSP) is an extension of the RCPSP where simultaneous scheduling of two or more projects which demand the same scarce resources is needed. Precedence constraints are usually defined only within projects. However, precedence relations between projects are also possible which would result in a program of interdependent projects as a special form of a sheer multi-project. Projects are linked by the usage of the same restricted resources of the company. An objective function on company level often has to be considered although objectives of single-projects may also be regarded. The company objective as e.g. maximizing profit is aimed at by managing the whole project portfolio or multi-project of the company by a resource manager, whereas project targets are set by single-project managers. The latter aim to minimize project delay, project cost, etc. the resource constrained multi-project scheduling problem with transfer times, is a generalization of the common RCMPSP [56] and a mixed-integer linear formulation found in [56].

IV. COMPUTATIONAL INTELLIGENCE: OVERVIEW

Nature and in particular biological systems have always been fascinating to the human experts due to its complexity, flexibility, and sophistication. Computational intelligence is relatively new to industry. It is still a fast- growing research area in the category of emerging technologies. On top of that, computational intelligence is based on a smorgasbord of approaches with very different theoretical bases, such as fuzzy logic, neural networks, evolutionary computation, statistical learning theory, swarm intelligence, and intelligent agents [57].

A fuzzy system is the component of computational intelligence that emulates the imprecise nature of human cognition. It mimics the approximate reasoning of humans by representing vague terms in a quantitative way. This allows inferring numerically in the computer with a different type of logic, called fuzzy logic, which is much closer to the real world than the classical crisp logic. In this way the computer ”knows” the meaning of vague terms, such as ”slightly better” or ”not very high” and can use them in calculating the logical solution. Contrary to common perception, the final results from fuzzy logic are not fuzzy at all. The delivered answers are based on exact numerical calculations [58].

The learning capabilities of computational intelligence are based on two entirely different methods - artificial neural networks and support vector machines. Artificial neural networks (ANN) are inspired by the capabilities of the brain to process information. A neural network consists of a number of nodes, called neurons, which are a simple mathematical model of the real biological neurons in the brain. The neurons are connected by links, and each link has a numerical weight associated with it. The learned patterns in the biological neurons are memorized by the strength of their synaptic links. In a similar way, the learning knowledge in the artificial neural network can be represented by the numerical weights of their mathematical links. In the same way as biological neurons learn new patterns by readjusting the synapse strength based on positive or negative experience, artificial neural networks learn by readjustment of the numerical weights based on a defined fitness function [59].

Support vector machines (SVM) deliver learning capabilities derived from the mathematical analysis of statistical learning theory. In many practical problems in engineering and statistics, learning is the process of estimating an

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unknown relationship or structure of a system using a limited number of observations. Statistical learning theory gives the mathematical conditions for design of such an empirical learning machine, which derives solutions with optimal balance between accurately representing the existing data and dealing with unknown data. One of the key advantages of this approach is that the learning results have optimal complexity for the given learning data set and have some generalization capability. In support vector machines the learned knowledge is represented by the most informative data points, called support vectors [60].

Evolutionary computation uses simulated evolution to automatically generate solutions of a given problem with a predefined fitness function. The process begins with creation in the computer of a random initial population of artificial individuals, such as mathematical expressions, binary strings, symbols, structures, etc. In each phase of simulated evolution, a new population is created by genetic computer operations, such as mutation, crossover, copying, etc. As in natural evolution, only the best and the brightest survive and are selected for the next phase. Due to the random nature of simulated evolution it is repeated several times before selecting the final solutions. Very often the constant fight for high fitness during simulated evolution delivers solutions beyond the existing knowledge of the explored problem [57]. The most notable evolutionary techniques for obtaining approximate solutions to optimization problems are genetic algorithms (GA) and scatter search (SS) and estimation of distribution algorithm (EDA).

Swarm intelligence mimics the social interactions of animal and human societies to explore the advantages of the collective behavior of an artificial flock of computer entities. A clear example is the performance of a flock of birds. Of special interest is the behavior of ants, termites, and bees. The approach is a new type of dynamic learning, based on continuous social interchange between the individuals. As a result, swarm intelligence delivers new ways to optimize and classify complex systems in real time. This capability of computational intelligence is of special importance for industrial applications in the area of scheduling and control in dynamic environments [57]. Two of the most notable swarm intelligence techniques for obtaining approximate solutions to optimization problems in a reasonable amount of computation time are ant colony optimization (ACO) and particle swarm optimization (PSO).

Intelligent agents are artificial entities that have several intelligent features, such as being autonomous, responding adequately to changes in their environment, persistently pursuing goals, and being flexible, robust, and social by interacting with other agents. Of special importance is the interactive capability of the intelligent agents since it mimics human interaction types, such as negotiation, coordination, cooperation, and teamwork. We can look at this technology as a modern version of AI, where knowledge presentation is enhanced with learning and social interaction. In the current environment of global wired and wireless networks intelligent agents may play the role of a universal carrier of distributed artificial intelligence [61].

Finally, various CI methods, such as fuzzy logic, neural networks, evolutionary computation, statistical learning theory, swarm intelligence, and intelligent agents have been applied to the RCPSP to overcome the drawbacks of exact optimal methods and priority-rule based heuristics and to improve the performance of the existing meta-heuristic methods [62].

V. CI IN RCPSP

For over fifty years now, the famous problem of RCPSP has been receiving the attention of researchers in operations research, engineering, and computer science. Over the past several years, there has been a spurt of interest in computational intelligence heuristics and metaheuristics for solving this problem. This Section and the following subsections seek to present a study of the state of the art in this field.

A. Fuzzy Systems

During project execution, however, project activities are subject to considerable uncertainty that may lead to numerous schedule disruptions. So we should consider this uncertainty in any realistic RCPSP approach. One of the major uncertainties is activity duration that may be difficult to predict accurately at the project early stage because a project is usually unique and "open-ended". There are two major approaches to handle uncertainty: stochastic and fuzzy. The latter one is especially well suited to handle such vague information. There are some papers concerned with fuzzy RCPSP mentioned below.

RCPS technique was developed for stochastic networks resource allocation decisions having imprecise duration of each activity with a known distribution function in which the values of activities finish times were determined at decision points when at least one activity was ready to be operated and there were available resources [63].

A fuzzy critical chain method was developed for project scheduling under resource constraints and uncertainty [64], in which consisted of developing a desirable deterministic schedule under resource constraints, and adding a project buffer to the end of the schedule to deal with uncertainty.

Fuzzy mathematical models were developed for determining construction schedules and for evaluating the contingencies created by crashing schedule time and delays due to unexpected material shortages. Multiobjective fuzzy mathematical models of project scheduling considering constraints such as time, cost, and unexpected resources shortages were used to minimize the project makespan using common methodologies. The research also developed a heuristic procedure for resource allocation [65].

A fuzzy random RCPSP was presented where the object of the problem was to find the optimally schedule project activities with fuzzy duration of using IP model that used the expected value of fuzzy random variables [66]. While RCPSP with fuzzy activity times was also modeled by proposing a measure for finding the non-integer power of a fuzzy number [67].

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B. Neural Network

Neural network was able to improve the performance of project scheduling by integrating feed-forward neural network into priority rule-based scheduling schemes to automatically select the suitable priority rules for each stage of project scheduling [68].

A hybrid of the adaptive-learning approach (ALA) was proposed for serial schedule generation and the augmented neural network (AugNN) approach for parallel schedule generation in solving the RCPSP problem [69]. In the AugNN approach, traditional neural networks were augmented in a manner that allows embedding of domain and problem-specific knowledge. The network architecture is problem specific and a set of complex neural functions were used to capture the constraints of the problem and apply a priority rule-based heuristic. The results were extremely competitive with other techniques such as genetic algorithms, simulated annealing, tabu search and sampling. A modified neural network to solve the multiprocessor scheduling problem with inequality constraints was presented [70].

C. Simulated Annealing

Electromagnetism (EM) optimization heuristic is a population-based method that is developed originally for optimizing unconstrained continuous functions based on an analogy with the electromagnetism theory [71]. At the right side, the effective extension of this electromagnetism metaheuristic to the RCPSP was illustrated [72]; showing how the RCPSP can be reformulated as an unconstrained optimization problem, they opted for a schedule representation in random-key (RK) format. Computational results showed that the procedure produces consistently good results, but hybrid metaheuristics outperform the EM procedure. Hence, they recommended that the incorporation of ideas from EM in hybrid frameworks contribute to the development of better meta-heuristic techniques.

The MORCPSP with renewable resources and two objectives, makespan and robustness, was modeled as the sum of the free slack of activities that should be maximized. They worked with only one renewable resource and aggregate the two objectives in a linear objective. SA was applied with a forward-backward recursion procedure [73].

Simulated annealing algorithm and genetic algorithm approaches were proposed as solution procedures to client-contractor bargaining problem in the context of the MRCPSPDCF with renewable resources only. Two payment models are analyzed: progress payments and payments at activity completion times. The bargaining objective is to maximize the bargaining objective function comprised of the objectives of both the client and the contractor. The bargaining objective function is expected to reflect the two-party nature of the problem environment, and seeks a compromise between the client and the contractor [74].

D. Tabu Search

Tabu search (TS) is a metaheuristic based on neighborhood search with overcoming local optimality. It was originally developed by Glover, [75], and a comprehensive report of the basic concepts and recent developments was given [76].

A comparison between SA and TS for solving the MRCPSPDCF and the maximization of the net present value of all cash flows was set [52]. They examined four common payment models: lump-sum payment at the completion of the project, payments at activities' completion times, payments at equal time intervals and progress payments. Computational experiments showed that SA outperformed TS for large number of activities. On the other hand, under a fixed number of activities, TS outperformed SA with the growth of the discount rate. Another approach proposed for the MRCPSP without nonrenewable resources is based on TS [77].

A multi-objective TS algorithm was presented to address bi-objective RCPSP with disruptions due to reworks and other undesirable conditions with two objectives - robustness maximization along with makespan minimization [78]. But the deficiency of the project schedule robustness measure was proved [79]. Moreover, Due to the serial generation scheme (SGS) used, the procedure can obtain good solutions in terms of makespan, but will probably miss all efficient solutions with (very) good robustness and probably not so good makespan.

A progressive resource allocation methodology was proposed to solve multi-objectives RCPSP based on multi-objective TS [80]. This technique explores the search space so as to find a set of potential efficient solutions without aggregating the objectives into a single objective function. It is guided by the principle of maximizing the usage of any resource before considering a replacement resource. Thus, a given resource is allocated to the maximum number of tasks for a given courses of action schedule. A good allocation is a potential efficient solution. These solutions are retained by applying a combination of a dominance rule and a multi-criteria filtering method. The performance of the proposed Pareto-based approach was compared to two aggregation approaches: weighted-sum and the lexicographic techniques. The result showed that a Pareto-based approach is providing better solutions and allowing more flexibility to the decision-maker.

Proactive scheduling aims at the generation of robust baseline schedules that are as much as possible protected against disruptions that may occur during project execution. The challenge a project manager has to deal with in an environment characterized by uncertain resource availabilities was viewed and a TS procedure was proposed to cope with the problem [81]. A focus on disruptions caused by stochastic resource availabilities and aim at generating stable baseline schedules was set [82]. A schedule's robustness (stability) was measured by the weighted deviation between the planned and the actually realized activity starting times during project execution. They presented a TS procedure that operated on a surrogate, free slack-based objective function.

A schedule-dependent setup time is defined as a setup time dependent on the assignment of resources to activities over time, when resources are, e.g., placed in different locations. In such a case, the time necessary to prepare the required resource for processing an activity depends not only on the sequence of activities but, more generally, on the locations in

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which successive activities are executed. A MRCPSP with schedule-dependent setup times was considered with nonpreemptable activities, renewable resources, and the objective was to minimize the project duration. TS was proposed to solve this strongly NP-hard problem [83]. The results of the computational experiment showed that TS was an efficient algorithm for solving the considered problem, clearly outperforming simple search algorithms: multi-start iterative improvement and random sampling. Nevertheless, for better evaluation of the proposed TS implementation, it has to be compared with more advanced methods, as well as with optimal solutions (or at least lower bounds) for smaller numbers of activities.

TS was used to solve a project scheduling problem where resources were employees and activity requirements were time-dependent. Furthermore, employees had different skills and legal constraints dictated by the French workforce legislation have to be respected. The project had to be scheduled and employees have to be assigned to activities, so that the maximal lateness was minimized. A linear programming model was formulated for the problem. Then, initial solutions to a TS algorithm were given by greedy algorithms [84].

In discrete-continuous project scheduling problems with discounted cash flows activities require for their processing discrete and continuous resources. The processing rate of an activity depends on the amount of the continuous resource allotted to this activity at a time. A positive cash flow is associated with each activity. This problem was considered with two common payment models-lump-sum payment and payments at activities' completion times. The objective was the maximization of the net present value of all cash flows of the project. TS was applied as well as simple search methods-multi-start iterative improvement and random sampling [85]. The work was extended by applying TS procedure for allocating the continuous resource to solve problems of scheduling non-preemptable, independent jobs on parallel identical machines under an additional continuous renewable resource to minimize the makespan [86]. The results produced by TS were compared with optimal solutions for small instances, as well as with the results generated by simple search methods - multi-start iterative improvement and random sampling for larger instances. And TS was compared with two other metaheuristics - SA and GA.

A number of dedicated exact reactive scheduling procedures as well as TS for repairing a disrupted schedule were proposed and evaluated, under the assumption that no activity can be started before its baseline starting time [87].

E. Evolutionary Computation

1) Genetic Algorithm: The GA technique simulates the evolution of living beings and incorporates the 'survival of the fittest' principle to solve complex optimization problems [88]. In a GA, processes loosely based on natural selection, crossover and mutation are repeatedly applied to a population that represents potential solutions. In recent decades, operations research literature has been overwhelmed with genetic algorithms for different project scheduling problems.

A GA model was proposed for resource allocation by developing a new crossover operator to avoid producing illegal chromosomes [89]. But GA was proposed to solve RCPSP with the objective of minimizing activities' cost where every activity is executed in single mode and the project has renewable resource-constraints as a result of the limited capacity of the partners [90]. GA was used to devise finance-based schedules in order to maximize project profit [91]. While, a parallel multiobjective GA framework was developed for the optimization in large-scale construction projects [92]. But evolutionary algorithms were attempted to be used to solve the RCPSP to minimize the project duration [93].

In modern manufacturing systems like multi-resource constrained project scheduling problem with the multiple modes (M-mRCPSP) is complicated because of the complex interrelationships between the units of the different stages. An adaptive genetic algorithm (aGA) was developed to solve the M-mRCPSP using priority-based encoding for activity priority and multistage-based encoding for activity mode and order-based crossover operator for activity priority and local search-based mutation operator for activity mode, the algorithm utilized iterative hill-climbing method in GA loop [53]. The numerical experiments showed that the proposed aGA is effective to the M-mRCPSP.

The double justification (DJ) can be easily incorporated into many diverse RCPSP algorithms, producing significant improvements in the quality of the schedules generated without generally requiring more computing time [94]. One of these algorithms was the GA activity list [95], a straightforward implementation of a GA with a general crossover operator. The new algorithm (termed DJGA), obtained after applying the double justification to each generated schedule of the GA, clearly outperformed the other state-of-the-art heuristics with an upper limit of 5000 generated schedules. These promising results gave the motivation to develop a hybrid genetic algorithm (HGA) [96], streamlining ideas and strategies already applied in the DJGA and other metaheuristics [97], [98]. HGA introduces several changes in the GA paradigm: a crossover operator specific for the RCPSP; a local improvement operator that is applied to all generated schedules; a new way to select the parents to be combined; and a two-phase strategy by which the second phase re-starts the evolution from a neighbor's population of the best schedule found in the first phase. The computational results show that HGA is a fast and high quality algorithm that outperforms algorithms of [94] and other state-of-the-art algorithms for the RCPSP.

Multiobjective resource allocation problem (MORAP) is the process of allocating resources among the various projects or business units to meet the expected objectives. Resources may be manpower, assets, raw materials, capital or anything else in limited supply which can be used to accomplish the goals. The goal may be objectives or targets (i.e., maximizing profits, minimizing costs, or achieving the best possible quality), usually driven by specific future needs. For this reason, the MORAP was formulated as a complex multiobjective optimization model. Hence, this problem was tackled via a multistage decision making model [99]. A multistage decision making model is similar to a complex problem solving, in which a suitable sequence of decisions is to be found. The task can be interpreted as a series of interactions between a decision maker and an outside world, at each stage of which some decisions are available and their immediate effect can be easily computed. Eventually, goals would be reached due to the found of optimized variables. In order to obtain a set of Pareto solutions efficiently, they proposed a multiobjective hybrid genetic algorithm (mo-hGA) approach based on the multistage decision making model. According to the proposed method, they applied the mo-hGA to seek feasible solutions for all stages. Another Pareto based multi-objective genetic algorithm NSGA-II was presented to solve multi-mode resource-constrained discrete time–cost-resource optimization model [100].

GA could be used for solving the RIP when tardiness is permitted with penalty [101]. The experimental results were satisfactory compared with other algorithms published. A resource investment problem with discounted cash flows (RIPDCF) is a project-scheduling problem in which the availability levels of the resources are considered decision variables and the goal is to find a schedule such that the net present value of the project cash flows optimizes. A new RIP was introduced where the goal was to maximize the discounted cash flows of the project payments and called it resource investment problem with discounted cash flows (RIPDCF) [102]. The cash flows may be either the project costs or the payments made for the project during its life cycle. In this regard, they considered both the payments and the employment-releasing times of the resources. They mathematically formulated the problem and showed that it is an NP-hard problem. In order to solve the model, they proposed a GA and examined the efficiency of the algorithm through some generated test problems. Then this work was extended where the RIPDCF in which the activities were subject to generalized precedence relations is first modeled and calls it RIPDCF/max [45]. Then, GA was proposed to solve this model. In addition, design of experiments and response surface methodology were employed to both tune the GA parameters and to evaluate the performance of the proposed method in 240 test problems. The results of the performance analysis showed that the efficiency of the proposed GA method is relatively well.

The generic framework of the RCPSP can be extended by the concept of alternative activities, to make its application in realistic disruption management (DM) problems possible: The x-RCPSP is based on a distinction between active and inactive activities as well as the definition of valid activity substitutions and associated constraints [103]. Beside the modeling framework, a GA was presented for the solution of the proposed generalization of the RCPSP. Its evaluation proved the fast convergence of schedule quality towards the optimal or at least a good solution.

Moreover, genetic algorithm could be used for solving the DTRTP with crossover points based on the resource utilization ratio, and also a local search method was incorporated with the algorithm [104]. Comparative computational results revealed that this procedure outperformed the TS approach [105].

A permutation-based elitist genetic algorithm was presented for solving the large-sized RCPSP in order to fulfill the lack of an efficient optimal solution algorithm for project networks with 60 activities or more as well as to overcome the drawback of the exact solution approaches for large-sized project networks [106]. The proposed algorithm employed the elitist strategy to preserve the best individual solution for the next generation so the improved solution can be obtained. A random number generator that provides and examines precedence feasible individuals was developed. A serial schedule generation scheme for the permutation-based decoding was applied to generate a feasible solution to the problem. But it was not clear if the proposed permutation-based algorithm was advantageous over traditional genetic algorithms and if it suited large-sized problems.

A steady-state genetic algorithm that used a dynamic population and codification methods was developed to evaluate the individuals that were generated via the application of the genetic operators [107]. These features allowed the algorithm to adapt itself to the characteristics of the problem. Computational results showed that the proposed scheduling method was one of the best scheduling techniques when compared with results reported in the literature.

Also, GA was presented to solve the resource constrained multi-project scheduling problem [108]. The chromosome representation of the problem was based on random keys. The schedules were constructed using a heuristic that built parameterized active schedules based on priorities, delay times, and release dates defined by the genetic algorithm. The computational results validated the effectiveness of the proposed algorithm.

GA was presented to solve RCPSP where an alternative representation of the chromosomes using a multi-array object-oriented model was used in order to take advantage of programming features in most common languages for the design of decision support systems [109]. The approach was tested on PSPLIB and computational results validated the effectiveness of the proposed algorithm and showed that our procedure equal most of previous results with less computational time.

The general discrete time/cost trade-off problem (DTCTP) was extended to a new multi-mode resource-constrained DTCTP model (MRC-DTCTP) in which renewable resource constraints were added to the problem [110]. By predefining the resource price, the renewable resources were related to the project costs, including direct cost and indirect cost. Every activity can be executed in the crashing way in which the project direct costs were used to shorten the activity duration. According to the characteristics of the MRC-DTCTP, a genetic algorithm for solving it was developed, and its effectiveness was verified by a comparison with an exact algorithm.

An evolutionary algorithm, known as differential evolution, was proposed [111]. In this approach a solution was represented by activity mode list. Neighbor solutions were generated using two operators: mutation and crossover. Selection operator used the values of the objective function which was penalized for solutions infeasible with respect to the nonrenewable resources. The performance of this algorithm was evaluated and compared with the results obtained by two other approaches only: simulated annealing [112] and particle swarm optimization [113]. Unfortunately, they were not compared with the results obtained by other more efficient algorithms.

The potential benefits of allowing one interruption when scheduling activities in a resource-constrained project were revealed [114].Then, the work was extended by defining a model for scheduling projects where activities have different numbers of allowed interruptions, also incorporating the possibility of restricting the minimum duration of the sub-

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activities and due dates [14]. An evolutionary algorithm was proposed for the new problem Maxnint-RCPSP, with a suitable codification and crossover. This algorithm can solve the m-PRCPSP, the problem in which each activity is allowed to be interrupted at most m times. In the computational experiments the algorithm was compared with HGA. They conclude that preemption seemed especially useful in the first steps of the algorithm when only few solutions are calculated. This made preemption very attractive for rescheduling.

HGA that used a powerful local search method was proposed for the MRCPSP [11]. The consideration of multiple modes for activities required this extension of the method that in addition to the change of the scheduling time usually implied the change of the execution mode looking for a new optimized position for each activity. The resulting method was applied to each feasible schedule drastically reducing its duration. But a two-phase genetic local search algorithm was developed where the same genetic local search algorithm run with different initial populations for both phases for different search purposes [115]. In the first phase, the initial population was generated randomly, and the set of good solutions (so-called elite set) was searched. In the second phase, the initial population contained mainly solutions from the elite set and the purpose of this phase was to search more thoroughly within the regions located by the solutions from the elite set. Computational experiment carried out and compared with five other algorithms: local search [116], SA [117], and three versions of genetic algorithms - [118], [119] and [120]. The presented results showed that the proposed two-phase genetic local search algorithm outperformed the other approaches.

A new GA algorithm was proposed to remedy the traditional RCPSP coding method in application [121]. A kind of chromosome encoding based on Activities Resource Competition Relation (ARCR) matrix was put forward. This algorithm makes it easier to solve the problem of crossover and mutation, meanwhile the code length and data structure of the coding method were studied. With the PSPLIB experiment data, finally, the results showed the feasibility and effectiveness of the genetic algorithm using the coding method.

Yet another implementation of a genetic algorithm was presented [15], in which two different populations of the same size were utilized: a population POPR that contains right-justified schedules only, and a population POPL that contains left-justified schedules only. A solution is encoded in the form of a topological ordering random key representation and a mode assignment list. A random key representation is a vector of priority values, and when topological ordering [94] is employed, priorities preserve precedence constraints. Serial SGS is used to construct a schedule during forward-backward scheduling. The forward procedure is applied to the left-justified population, and is used to build a right-justified schedule. Next, the completion times of activities are used as the priority values for the random key representation, and each activity is scheduled as late as possible. Genetic operators are then applied to the right-justified schedules, and the backward procedure runs for the obtained population of right-justified schedules. A mode improvement procedure runs together with serial SGS. This procedure is applied with a given probability to activities of the project, and checks for a chosen activity if the change of the assigned mode leads to an earlier completion time of this activity without increasing the penalty function value. The penalty function is calculated for the nonrenewable resources consumption that exceeds resource availability limitations. Two fitness functions are investigated [119] and [120]. The offspring solutions are generated using 2-tournament selection, one-point crossover, and two mutation operators (one acting on the mode assignment list, and the other acting on a random key vector). The performance of the proposed algorithm is compared with the performance of other approaches including: the genetic algorithms [118], [119] and [120], as well as the local search [116], and SA [117]. The obtained results showed that the considered genetic algorithm approach was the most powerful heuristic developed up to now.

GA for the RCPSP was presented [122]. The chromosome representation of the problem is based on random keys. The schedule is constructed using a heuristic priority rule in which the priorities of the activities are defined by the genetic algorithm. The heuristic generates parameterized active schedules. The approach was tested on a set of standard problems taken from the literature and compared with other approaches. The computational results validate the effectiveness of the proposed algorithm. While a new GA for RCPSP was presented [123]. The algorithm employs a standardized random key (SRK) vector representation with an additional gene that determines whether the serial or parallel schedule generation scheme (SGS) is to be used as the decoding procedure. The iterative forward-backward improvement as the local search procedure is applied upon all generated solutions to schedule the project three times and obtain an SRK vector, which is reserved into population. Several evolutionary strategies are implemented including the elitist selection (the high quality solution set), and the selection of parents used in crossover operator. The computational experiments showed that the proposed algorithm outperforms the current state-of-the-art heuristic algorithms only in small project sizes. But a biased random-key GA was employed for the RCPSP [124]. The chromosome representation of the problem is based on random keys. The schedules are constructed using a priority rule in which the priorities are defined by the genetic algorithm. Schedules are constructed using a procedure that generates active schedules. The approach is tested on a set of standard instances taken from the literature and compared with results of 25 other algorithms taken from the literature. Overall, the experiments validate the effectiveness of the proposed algorithm.

An issue has arisen with regard to which of the schedule generation schemes will perform better for an arbitrary instance of the RCPSP. No general answer has been given to this issue due to the different mechanisms between the serial scheme and the parallel scheme. In an effort to address this issue, a comparison between the two schemes using a permutation-based elitist GA for the RCPSP was conducted [125]. From the results of a paired difference experiment, the algorithm using the serial scheme provides better solutions than the one using the parallel scheme. The results also show that the algorithm with the parallel scheme takes longer to solve each problem than the one using the serial scheme. Preemptive RCPSP with makespan minimization was tackled by a genetic algorithm which showed that the proposed algorithm was amongst the most competitive algorithms in literature for the preemptive cases [126]. While a GA was proposed with a local search strategy in its operators to solve RCPSP minimizing the project makespan [127]. Extensive numerical experiments showed that the proposed GA with neighborhood search was efficient in aspects of solution quality and computational time compared with existing algorithms in the RCPSP literature, especially for the instances with a large number of activities.

A new evolutionary algorithm (EA) was developed to cope with nonpreemptive MRCPSP, where the objective is the minimization of the project duration [128]. The satisfaction of the nonrenewable resource constraint is relaxed into an additional penalty objective to be minimized. Therefore, the original single objective problem is transformed into a bi-objective one. In order to avoid premature convergence in this bi-objective search space, the EA is enhanced by the use of an adaptive grid, relying on clustering techniques. The latter issue is quite innovating and appears to be promising in general multiobjective combinatorial optimization. The role of the crossover operator during the evolutionary search of the MRCPSP solution is emphasized via a new crossover operator that uses genetic material from the best individual obtained by the search process besides genetic information from the parents [129], i.e., the precedence feasibility of solutions is preserved in offspring if both parents and global best represent feasible solutions.

An extension of the MRCPSP to its version with generalized precedence relations (also called time windows), denoted as the MRCPSP-GPR (or MRCPSP-max), and is studied in several publications. MRPCPS/max is a very general and difficult problem that can model many practical applications within project scheduling, due to its characteristics like multiple modes, non-renewable resources or maximum time lags. Project scheduling problems of this type occur e.g. in process industries. A double GA was proposed for the MRCPSP-max which outperforms other state-of-the-art approaches in medium and large instances [13]. This version of a genetic algorithm consists of two-phases. In the first phase algorithm searches for the best modes of the activities, and in the second phase the makespan is minimized. For each phase different parameters and mechanisms are defined including representation, fitness, operators, etc.

Recently, a GA is developed for RCPSP with mode identity, in which a set of activities is partitioned into disjoint subsets, while all activities forming one subset have to be processed in the same mode [130]. The objective is to schedule the activities, in order to minimize the project duration. GA shows competitive results with B & B as the amount of computational time for the proposed methods was much less than that required by B & B. An adaptive GA was presented by Ponz-Tienda et al. [131] for solving the resource leveling problem, using the Weibull distribution to establish an estimation of the global optimum as a termination condition, allowing the extension of the project deadline with a penalty and avoiding the increase in the project criticality. The proposed algorithm is implemented to provide a flexible and powerful decision support system that enables practitioners to choose between different feasible solutions to a problem in realistic environments.

2) Scatter Search: The scatter search (SS), is an evolutionary method that has been successfully applied to combinatorial and non-linear optimization problems [132]. In contrast to other evolutionary methods such as genetic algorithms, the SS is founded on the premise that systematic designs and methods for creating new solutions afford significant benefits beyond those derived from recourse to randomization. The SS strategies for search diversification and intensification have proved to be effective in a variety of optimization problems [133]. However, there are few applications of the SS to the RCPSP. A hybrid scatter search/electromagnetism meta-heuristic for the RCPSP was presented [72]. Several variants of the SS were implemented for the resource availability cost problem (RACP) and the experimental results showed that the SS is capable of providing high-quality solutions for the RACP in a reasonable computational time [134]. Subsequently, a SS for the resource availability cost problem with scenarios (RACPS) was developed [135]. But SS algorithm was used to tackle the discrete time/resource trade-off project scheduling problem, the computational results of which verified the efficiency of the algorithm [37]. Additionally, an enhanced scatter search (ESS) was proposed to solve the RCPSP [136]. Recently, a novel solution representation based on an ordered list of events was proposed, that are sets of activities that start at the same time and an evolutionary algorithm operates on the event list and relies on a scatter search framework for solving the RCPSP [137]. Computational results on benchmark instances of the literature indicated that the proposed algorithm got high quality solutions.

F. Swarm Intelligence

1) Ant-Colony Optimization: Recently, a new class of metaheuristics inspired by the behavior of ant colonies was developed, called Ant Colony Optimization (ACO) algorithms [138]. In ACO algorithms, artificial ants stepwise build solutions by making probabilistic decisions based on local information. At each step, an ant chooses one possibility from a set of feasible options, thus progressing towards a complete solution. Although promising results have already been achieved for many types of problems, the applicability of ACO for the RCPSP has also been thoroughly investigated.

A hybrid ant colony optimization (HACO) was proposed, in which both the solution construction mechanism of branch and bound (B&B), and ACO algorithms are hybridized [139]. First, B&B is used to find a set of feasible (i.e. satisfying nonrenewable resource constraints) mode assignments. For each feasible mode assignment the following procedure is applied. Firstly, CPM is used to calculate the schedule length when the resource constraints are neglected. Secondly, a disjunctive rule is applied to add some arcs to the AoN network in order to remove resource conflicts. Thirdly, a new project makespan is calculated for the new AoN network representing the structure of the project. Next, a given number of mode assignments with the best potential values (the makespan obtained during the third step of above mentioned procedure) are chosen for the second phase of H-ACO where the ACO algorithm with the forward-backward improvement is applied to each chosen mode assignment. Finally, the best schedules obtained by ACO for each chosen mode assignment are compared, and the best one is chosen as a solution of the considered instance of the problem. H-

ACO is compared with SA using the standard data sets from PSPLIB [117]. The obtained results show that H-ACO outperforms SA.

The nonlinear resource allocation problem addresses the important issue which seeks to find an optimal allocation of a limited amount of resource to a number of tasks for optimizing a nonlinear objective over the given resource constraint. ACO algorithm was presented for conquering the nonlinear resource allocation problem incorporating adaptive resource bounds to guide the search [139]. The experimental results manifested that the proposed method is more effective and efficient than a genetic algorithm. Also, this method converges at a fast rate and a reliable performance guarantee was provided through a worst-case analysis. A modified ACO approach to RCPSP was presented and evaluated in which the latest stating time of each activity is modified in the dynamic rule for each iteration [140]. Modifications to the basic ACO algorithm, case studies, and sensitivity analysis were presented [141]–[143]. A new methodology to schedule resource-constrained construction projects by use of algorithms based on ACO was presented; the work presented builds on previous work on critical path calculations by use of ACO [141], [142] and presents a methodology to extend the ACO solution algorithms to account for resource-constrained construction sequences [144].

A multi-objective RCPSP with a multimode feature and renewable resources was developed [145]. The objectives of the RCPSP are namely: the minimization of the makespan, the minimization of the total cost and the maximization of the probability of success. For that, they developed an Ant System based approach based on multi-objective concepts to schedule the set of tasks while assigning the suitable modes.

ACO was proposed to solve resource allocation in repetitive construction schedules constrained by the activity precedence and multiple resource limitations in order to minimize the overall project duration as well as the number of interruption days [146]. The proposed approach can be included in the list of reliable and useful optimization tools for solving such problems.

An ant algorithm with dual ant colonies was proposed to improve the effective allocation of project resources [147]. The algorithm adaptively adjusts resource allocation according to the pheromone updated by artificial ants employed to search for feasible schedules. Two separate ant colonies are employed. The forward scheduling technique is applied by one ant colony while the backward scheduling technique is applied by another ant colony. The pheromone information of the two ant colonies is exchanged periodically to avoid early local convergence. An experimental testing indicates that the new design of two separate ant colonies with different scheduling techniques helps to improve the performance of resource constrained project scheduling.

The resource-constrained multiprocessor scheduling problems (RCMPSP) is a general scheduling problem. The major difference between RCMPSP and RCPSP is that RCMPSP has a special resource type - processors (or machines), and one processor can only process one job (activity) at a time. A modified ACO approach was presented and evaluated for the precedence and (RCMPSP) [148]. The proposed method can be applied to solve RCPSP directly without modification. Simulation results demonstrated that the proposed algorithm provided an effective and efficient approach for solving multiprocessor system scheduling problems with resource constraints.

A modified version of ACO was proposed to solve multiobjective resource allocation problem MORAP in order to obtain a set of Pareto solution efficiently, in this algorithm we try to increase the efficiency of algorithm by increasing the learning of ants [149]. Experimental results manifest that the proposed ACO-based method outperforms the genetic algorithm on a set of simulated MORAP problems.

ACO was proposed to solve MRCPSP [150]. The performance of the algorithm was checked on the basis of a computational experiment by comparing the obtained results with the results provided for other best state-of-the-art algorithms. The presented results showed that the ACO outperforms the other approaches. But, ACO algorithm was presented for the RCPSP that uses dynamic pheromone evaporation to forget suboptimal solutions that gathered enough pheromone along them to attract other ants unnecessarily [151]. In spite of the computational results showed better results advancements could be done via hybridizing the algorithm with GA.

As a class of evolutionary computation or artificial evolution, the artificial bee colony (ABC) algorithm is a metaheuristic intelligence optimization algorithm that motivated by the intelligent behavior of honey bees, and based on bee foraging model was proposed [152]. ABC algorithm with random key was proposed for RCPSP in real time minimizing the makespan [153]. The artificial bee colony algorithm (named by ABC-RK) for this problem was modified, where the problem representation was based on random key, and a heuristic priority rule to assign activities was also employed. The preliminary experimental results showed that ABC-RK is capable of providing near-optimal solutions for a small scale RCPSP and large scale problems. But further studies needed to focus on enhancing the applicability and efficiency of the proposed ABC-RK algorithm for large-scale instances of RCPSP. Also, the application of bee algorithms (bee algorithm (BA), artificial bee colony (ABC), and bee swarm optimization (BSO)) were investigated for RCPSP [154]. The performances of the proposed algorithms were compared against a set of state-of-art algorithms. The simulation results showed the efficiency of bee algorithms for solving RCPSP and produce competitive results compared to other algorithms.

An ant colony system (ACS) algorithm is proposed to solve the general MRCPSPDCF with cash inflows and outflows [16]. In the presented algorithm, the AoA network of the problem is first converted into a mode-on-node (MoN) graph, which next becomes the construction graph for the ACS algorithm. Based on the construction graph, the authors apply the serial SGS for artificial ants to explore the solutions to the problem. In the process of this algorithm, each ant maintains a schedule generator and builds its solution by selecting arcs on the graph using pheromone and heuristic information. Eight different domain-based heuristics are developed to enhance the search skill of ants by considering the factors of time, cost, resources, and precedence constraints. The proposed ACS approach is compared with the authors'

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implementations of GA [51], as well as SA and TS [52], the authors stated that their algorithm outperforms the other three metaheuristics.

2) Particle Swarm Optimization: PSO simulates a social behavior such as birds flocking to a promising position for certain objectives in a multidimensional space [155], [156]. In PSO, a swarm of particles spreads in the space and the position of a particle represents a solution of a dedicated problem. Each particle would move to a new position based on the global experience of the swarm and the individual experience of the particle for the global optimum. Like evolutionary algorithm, PSO conducts its search using a population, called a swarm, of individuals, called particles. Each particle represents a candidate position or solution to the problem at hand, resembling the chromosome used by GA. In contrast to GA's crossover or mutation for reproducing next generations of chromosomes, during searching for optima each PSO particle adjusts its trajectory towards its own previous best position, and towards the best previous position attained by any member in the swarm. Thus, global sharing of information takes place and particles profit from their own discoveries (i.e., local bests) and the previous experience of all other companions (i.e., global bests) during the search process.

PSO was presented to develop a solution-solving scheme for the RCPSP [157]. The potential solution to the RCPSP in view of minimizing project duration is represented by the multidimensional particle, where two solution representations, i.e., priority-based representation and permutation-based representation, are respectively considered. The computational analyses demonstrate that the permutation-based PSO outperforms the priority-based PSO and that the PSO-based methodology has good performance as other metaheuristic methods such as GA and SA do in solving the RCPSP. The PSO algorithm was shown to converge a little faster than GA, and PSO had a more stable tendency than GA while searching for optima [158], [159]. Furthermore, PSO was "more robust than general analytical and heuristic methods, because it does not lead to combinatorial explosion or problem-dependent effectiveness" [157]. Also, PSO was used to solve RCPSP; they showed that the PSO is applicable to various combinatorial problems and scheduling problems [160] and [161]. While an attempt was provided to make use of preemption and break for the resource-constrained construction project with the objective of minimizing project duration and introduced a PSO-based methodology to solve such problem [162]. The problem under study allows the preemptive activities to be interrupted in off-working time and not to resume immediately in the next working period because all the limited resources are to be reallocated during a break. The potential solution to the PSBRC, i.e., a set of priorities deciding the order to start the activities or restart the interrupted activities, is represented by the multidimensional particle position. Hence PSO is applied to search for the optimal schedule for the PSBRC, in which a parallel scheme is adopted to transform the particle-represented priorities to a schedule.

A PSO algorithm was presented for solving RCPSP with an extension of the PSO system is proposed, that integrated a new displacement of the particles and a relation between the coefficients for each dimension between the classical PSO algorithm and the extension was highlighted [163]. The experiments on instances from the PSPLIB showed that the proposed PSO algorithm was able to solve to optimality most problems of the series and close to the best known solutions on the hardest instances. This indicated that this general algorithm was a good candidate for solving scheduling problems.

A combinatorial particle swarm optimization (CPSO) is used to generate solutions of the mode assignment sub problem of the MRCPSP [113]. Next, for a fixed mode assignment, a local search algorithm is used to find suboptimal solutions of the resulting RCPSP. A computational experiment is carried out for seven data sets from PSPLIB containing instances with 10-30 activities. The results obtained by the proposed approach are compared with results generated by two other approaches only, namely the SA [112] and PSO [162], and show that the proposed approach performs better than the two other approaches.

Distributed task scheduling problems generalized as a distributed version of the Resource-Constrained Project Scheduling Problem (DRCPSP) was addressed [164]. They applied and evaluated an algorithm called Swarm-DRCPSP that used a probabilistic decision model, based on paradigms from swarm intelligence such as the tendency social insects have for performing certain tasks. They showed that Swarm-DRCPSP performs better than a distributed greedy algorithm, and that this performance is not much far from the best known solutions for the RCPSP, with the advantage of being computed in a distributed way.

An improved PSO algorithm was presented to solve RCPSP by adding a mapping between the feasible schedule and the position of the particle, then the PSO begin to search the global best and the local best until the stop criteria is satisfied [165]. The computation analysis show that the approach based on IPSO has the ability to search for the global optima, and is more efficient than the traditional PSO method and GA approach. Static and dynamic population topologies for a PSO were analyzed for non-preemptive single mode RCPSP in order to minimize the project makespan [166]. The algorithm incorporates well-known procedures such as the serial schedule generation scheme and forward-backward improvement. The reported results from computational experiments using a benchmark set of problem instances demonstrated that the proposed particle swarm optimization approach is competitive. It was shown that the population topology has a significant influence on the performance of the algorithm.

A PSO approach with two proposed rules named delay local search rule and bidirectional scheduling rule was proposed to solve the RCPSP in order to minimize the project makespan [167]. The delay local search enables some activities delayed and altering the decided start processing time, and being capable of escaping from local minimum. The bidirectional scheduling rule which combines forward and backward scheduling to expand the searching area in the solution space for obtaining potential optimal solution. Moreover, to speed up the production of feasible solution, a

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critical path is adopted in this study. The critical path method is used to generate heuristic value in scheduling process. The simulation results reveal that the proposed approach in this investigation is novel and efficient for resource-constrained class scheduling problem.

A mathematical model for the multiobjective MRCPSP with positive and negative cash flows with bi-objectives was introduced, the first objective is maximization of the NPV and the second one is minimization the makespan and floating time (i.e., maximization of robustness) [168]. A multiobjective Pareto archive PSO with the peak crossover and the local search based mutation was proposed to solve this formulated model and compared with the conventional multiobjective evolutionary algorithm, known as NSGA-II. The experimental results have indicated that the proposed PSO outperformed the NSGA-II. Justification PSO was proposed [169]. The justification technique adjusts the start time of each activity of the yielded schedule to further shorten the makespan. Experimental results indicated that the proposed algorithm was an effective and efficient approach for solving RCPSP.

G. Other Metaheuristics

JADE-based A-Team environment (in short: JABAT) is a middleware supporting the construction of the dedicated A-Team architecture that can be used for solving variety of computationally hard optimization problems. An overview of the JABAT providing architecture designed to solve RCPSP and MRCPSP instances was presented [170]. To construct the proposed system a number of agents, each representing a different optimization algorithm including local search, TS, as well as several specialized heuristics have been used. The proposed agent-based approach produced good or very good solutions which are competitive or even outperform other population-based approaches. The application of JABAT was extended to solve RCPSP-max and showed it efficiency to solve the problem [171] and [172].

A restart evolution strategy (RES) for the RCPSP was presented, as well as its integration in a multi-agent system (MAS) for solving the decentralized resource-constrained multi-project scheduling problem (DRCMPSP) [173]. The RES found better solutions than the best ones found so far for the RCPSP. In addition, the MAS is suitable for solving large multi-project instances decentrally. The results for the DRCMPSP showed that the presented decentralized MAS was competitive with a central solution approach. Moreover, For the DRCMPSP considered, other MAS is available in the literature [174]. This system is based on modern electronic auctions for resource allocation and simple heuristics for scheduling activities. The methods were used for small multi-project instances.

Each activity was considered as an autonomous agent and process can be carried out by using MAS [175]. The effective resource allocation process depends on task interdependencies, resource interdependencies and constraints. Crucial for the multi-agent coordination in project scheduling is the availability of an effective algorithm for resource allocation. MAS is successful only if the agents in the system are ready to cooperate and there arises a need for resource allocation among competitive multiple agents. They proposed a model for resource allocation based on priority rules in order to minimize the project duration by overlapping the activities of the project. Therefore, an integrated planning and scheduling algorithm has been developed and employed for better resource allocation and task scheduling to minimize the project makespan. The results clearly showed that the developed system was capable of producing consistently good results for the resource-constrained project scheduling. A new lower bound for RCPSP was found using energetic reasoning based on new integer programming (IP) formulations [176]. And the work was extended by finding better lower bounds which outperformed the classical energetic reasoning-based lower bound [177]. Recently, a new MAS is developed for solving distributed RCMPSP. Experimental results demonstrated its ease, fast and flexibility in dealing with the dynamicity of the project [178].

Population learning algorithm (PLA) is a population-based method inspired by analogies to a phenomenon of social education processes in which a diminishing number of individuals enter more and more advanced learning stages [179]. The effectiveness of applying PLA to solving both RCPSP and MRCPSP with makespan minimization as an objective function was shown [180].

Artificial Immune System (AIS) can be defined as an abstract or metamorphic computational system using ideas gleaned from the theories and components of immunology [181]. AIS approach was proposed to solve RCPSP with an objective of minimizing the makespan of a project [182]. It exploits the beauty of learning and memory acquisition to ensure the convergence with faster rate. It is found that the performance of the AIS was superior as compared to GA, fuzzy-GA and other metaheuristic based approaches. AIS proved its effectiveness as problem solving technique for the MRCPSP [31]. But AIS when used to solve RCPSP with makespan minimization as the objective had showed competitive results in comparison with the existing benchmark algorithms inspiring for solving real-world problems [183]. Chaos-based improved immune algorithm (CBIIA) was proposed for solving RCPSP with the objective of minimizing project makespan [184]. The proposed CBIIA is based on the traits of an AIS, chaotic generator and parallel mutation. CBIIA is different from the traditional immune algorithm in its initialization and parallel mutation mechanism. The efficacy of the proposed algorithm is showed by Patterson's test.

Iterative flattening search (IFS) is a scalable procedure for solving multi-capacity scheduling problems [185]. Given an initial solution, IFS iteratively applies: (1) a relaxation-step, in which a subset of scheduling decisions are randomly retracted from the current solution; and (2) a flattening-step, in which a new solution is incrementally recomputed from this partial schedule. Whenever a better solution is found, it is retained, and, upon termination, the best solution found during the search is returned. Prior research has shown it to be an effective and scalable heuristic procedure for minimizing schedule makespan in multi-capacity resource settings. IFS is applied to solve RCPSP and experimentally investigated the impact on IFS performance of algorithmic variants of the flattening step [186]. The variants considered are distinguished by different computational requirements and correspondingly vary in the type and depth of search performed. The analysis is centered around the idea that given a time bound to the overall optimization procedure, the IFS optimization process is driven by two different and contrasting mechanisms: the random sampling performed by iteratively applying the ”relaxation/flattening” cycle and the search conducted within the constituent flattening procedure. On one hand, one might expect that efficiency of the flattening process is key: the faster the flattening procedure, the greater the number of iterations (and number of sampled solutions) for a given time bound; and hence the greater the probability of finding better quality solutions. On the other hand, the use of more accurate (and more costly) flattening procedures can increase the probability of obtaining better quality solutions even if their greater computational cost reduces the number of IFS iterations. Comparative results on well-studied benchmark problems are presented that clarify this tradeoff with respect to previously proposed flattening strategies; identify qualitative guidelines for the design of effective IFS procedures.

A hybrid of branch-and-bound procedure and memetic algorithm was developed to tackle the nonpreemptive-MRCPSP with nonrenewable resources. The objective was to schedule the activities to maximize the expected NPV of the project, taking into account the activity costs, the activity durations, and the cash flows generated by successfully completing an activity; to enhance both mode assignment and activity scheduling [186]. Algorithmic performance is rated on the maximization of the project NPV and computational results showed that the two-phase hybrid metaheuristic performs competitively for all instances of different problem sizes.

The shuffled frog-leaping algorithm (SFLA) combines the benefits of genetic-based memetic algorithm (MA) and the social behavior-based PSO algorithm [187].The effectiveness of using SFLA for solving the MRCPSP with the criterion to minimize the makespan was approved [188]. It was found that SFLA needs a very careful choice of its parameter in order to be effective [189].

Estimation of distribution algorithm (EDA) is a kind of stochastic optimization algorithm based on statistical learning [190]. Unlike GA explicitly applies crossover and mutation operator to generate new individuals, EDA generates new individuals by predicting the most promising area based on the distribution of elite individuals of former generations in the search space. EDA was proposed to solve RCPSP and MRCPSP with the criterion to minimize makespan [191] and [192]. Computational results and comparisons demonstrated the effectiveness of the EDA.

VI. HYBRID COMPUTATIONAL INTELLIGENCE

In the last few years several heuristic, metaheuristic and hybrid CI techniques have been developed to solve RCPSP, most of them use the standard activity list representation.

The RCPSP with fuzzy activity duration and fuzzy deadline was studied. On the basis of the concept of schedule robustness for fuzzy deadline and fuzzy project makespan, a GA based on activity list representation was proposed for solving this problem [193]. The computational experiment showed that the performance of the proposed GA is better than GA appearing in the literature. A hybrid genetic algorithm with fuzzy logic controller (flc-hGA) was proposed to solve the resource-constrained multiple project scheduling problem (RCMPSP) which is well known NP-hard problem [194]. Objectives described in their paper are to minimize total project time and to minimize total tardiness penalty. However, it is difficult to treat the RCMPSP problems with traditional optimization techniques. The proposed new approach is based on the design of genetic operators with fuzzy logic controller (FLC) through initializing the revised serial method which outperforms the non-preemptive scheduling with precedence and resources constraints. For these rc-mPSP problems, it was demonstrated that the proposed flc-hGA yields better results than conventional genetic algorithms and adaptive genetic algorithm. The flc-hGA was extended to solve RCMPSP with a mixed uncertainty of fuzziness and randomness [195], and applied to solve the working procedure in a large-scale water conservancy and hydropower construction project in the southwest region of China. Practical results indicate that both the proposed model and the flc-hGA are viable and efficient in handling such complex problems. RCPSP with fuzzy processing time and fuzzy due date was studied where the objective was to maximize the scheduling robustness [196]. GA with activity list representation is proposed for solving this problem. The computational experiment shows that the performance of the proposed algorithm is better than the existing correlation algorithm, and there is no difference between the two weak comparison methods on the performance of the algorithm. A representation was designed to allow inclusion of a lot of problem-specific knowledge [197]. Based on that representation a new competitive and robust hybrid genetic algorithm has been developed, which used genetic operators and an improvement mechanism specially designed to work on that representation and exploit the information contained in it. Unfortunately, the developed algorithm is not advisable for large projects. An adjusted fuzzy dominance genetic algorithm was presented to solve multi-mode resource-constrained DTCTP model [198]. The performance of the proposed algorithm shows its superiority over the performance of well-known multiobjective algorithms.

Masmoudi and Haït [199] have presented a fuzzy model for project scheduling problems. A GA is generalized to solve Fuzzy Resource Leveling problem and a Parallel SGS is generalized to solve Fuzzy RCSPS problem.

A hybrid metaheuristic ANGEL was presented for RCPSP. ANGEL combines ACO, GA and local search strategy [200]. The procedure of ANGEL is as follows. First, ACO searches the solution space and generates activity lists to provide the initial population for GA. Next, GA is executed and the pheromone set in ACO is updated when GA obtains a better solution. When GA terminates, ACO searches again by using a new pheromone set. ACO and GA search alternately and cooperatively in the solution space. An efficient local search procedure is applied to yield a better solution when ACO or GA obtains a solution. A final search is applied upon the termination of ACO and GA. The experimental results of ANGEL on the standard sets of the project instances showed that ANGEL was an effective method for solving the RCPSP.

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A hybrid PSO with a particle-updating mechanism incorporated with a partially mapped crossover of GA and a definition of an activity-move-range was developed in order to handle the permutation-based representation for the RCPSP [158]. The particle-represented sequence should be transformed to a schedule (including start times and resource assignments for all activities) through a serial method and accordingly evaluated against the objective of minimizing project duration. However, unlike GA, which needs to predefine the crossover probability and performs crossover between two unclassified survivals or individuals, the hybrid PSO shows some advantages over GA, such as "one-way" sharing of the local best and the global best experiences during the search process and easy adjusting of a few parameters for satisfied results.

A parallel intelligent search technique named the fuzzy-based adaptive sample-sort simulated annealing heuristic was proposed [201]. The basic ingredients of the proposed hybrid algorithm are the serial schedule generation scheme (SGS); sample-sort simulated annealing (SSA), and the fuzzy logic controller (FLC). The serial SGS generates the initial schedules following both the precedence and resource constraints. SSA is basically a serial simulated annealing algorithm, artificially extended across an array of samplers operating at statistically monotonically increasing temperatures. The FLC makes the SSA adaptive in nature by regulating the swapping rate of an activity's priority during an improved schedule generation process. The implementation results of the algorithm revealed its superiority over most of the currently existing approaches.

Path relinking is an evolutionary method proposed to integrate intensification and diversification strategies in the context of TS [76]. In this approach, new solutions are generated by searching trajectories that connect two elite solutions, by starting from one of these solutions, calls the initial solution, and generating a path in the neighborhood space that leads toward the other solution, called guiding solution. In this path, the moves are selected that introduce attributes contained in the guiding solution. TS based heuristics with path relinking was developed for the MRCPSP [12]. Path relinking is used as a post optimization strategy; so that it explores paths that connect elite solutions found by the TS based heuristics. Computational results show that path relinking is able to improve the TS based heuristics, but unfortunately the proposed method was not compared with efficient algorithms appeared in literature.

A project scheduling problem with the objective of minimizing resource availability costs required to execute the activities in a project by a given project deadline was considered [201]. The project contains activities interrelated by finish-start-type precedence relations with a time lag of zero, which require a set of renewable resources. Two metaheuristics, path relinking and genetic algorithm, were developed to tackle this problem in which a schedule is created with a precedence feasible priority list given to the schedule generation scheme. In these procedures, each new generation of solutions are created using the combination of current solutions. Comparative computational results revealed that path relinking was a very effective metaheuristic and dominated genetic algorithm.

A new hybrid metaheuristic algorithm was presented to solve the discrete time/resource trade-off problem with multiple resources (MDTRTP); the new metaheuristic algorithm is based on scatter search and path relinking methods [37]. In the SS algorithm for the MDTRTP, they use path relinking concepts to generate children from parent solutions, in the form of a new combination method. They also incorporate new strategies for diversification and intensification to enhance the search, in the form of local search and forward-backward scheduling, based on so-called reverse schedules, with the activity dependencies reversed. The proposed algorithm is also modified to tackle the RCPSP and MRCPSP. The performance of the algorithm is tested on four data sets, which show that in most cases it outperforms the other heuristic approaches presented in the literature.

Multi-mode project payment scheduling problem where the activities can be performed with one of several discrete modes and the objective is to assign activities' modes and progress payments so as to maximize the net present value of the contractor under the constraint of project deadline. The event-based method was used to construct the basic model of the problem and in terms of the different payment rules it was extended as the progress based, expense based, and time based models further [203]. For the strong NP-hardness of the problem; authors developed SA and TS algorithm, to solve the problem. The experimental results showed that the proposed algorithm seemed to be the most promising algorithm for solving the defined problem especially when the instances become larger.

A hybrid of GA and SA (GA-SA Hybrid) was proposed to tackle multi-project scheduling problems with multiple resource constraints. The proposed GA-SA Hybrid was compared to the modified simulated annealing method (MSA), which is more powerful than GA and SA [204]. As both GA and SA are generic search methods, the GA-SA Hybrid is also a generic search method. The random-search feature of GA, SA and GA-SA Hybrid makes them applicable to almost all kinds of optimization problems. Experimental analysis showed that GA-SA Hybrid has better performance than GA, SA, MSA, and some most popular heuristic methods.

RCPSP with fuzzy activity duration times was discussed [205], building three types of fuzzy models to minimize the total cost. They also design a hybrid intelligent algorithm integrating fuzzy simulation and GA to deal with the project scheduling problem with fuzzy constraints. And it is revealed that the algorithm is an effective tool to solve this type of project scheduling problem.

A hybrid algorithm that combines advantages of ACO and NN was proposed to solve resource-constrained multi-project scheduling (RCMPS) [206]. The experimental results show that the new algorithm effectively relieves the disadvantages of ACOA and NN in RCMPS. A hybrid of ACO and SS was proposed to solve RCPSP [207]. The proposed algorithm was compared with state-of-the-art algorithms using a set of standard problems available in the literature. The experimental results validated the efficiency of the proposed algorithm. While, a hybrid algorithm of SS and path relinking was presented to solve RCPSP in PERT networks (where activities require resources of various types with random duration) minimizing projects makespan [208]. The efficiency of the new hybrid metaheuristic algorithm showed by comparing its solutions with optimal solution for small networks and also applied to test problems available on the PSPLIB.

A neurogenetic approach which is a hybrid of GA and NN approaches was proposed. In this hybrid approach the search process relies on GA iterations for global search and on NN iterations for local search [209]. The GA and NN search iterations are interleaved in a manner that allows NN to pick the best solution thus far from the GA pool and perform an intensification search in the solution's local neighborhood. Similarly, good solutions obtained by NN search are included in the GA population for further search using the GA iterations. Although both GA and NN approaches, independently give good solutions, they found that the hybrid approach gives better solutions than either approach independently for the same number of shared iterations.

A hybrid EDA with a new local search based on random walk and the delete-then-insert operator was proposed for solving MRCPSP [210]. The proposed algorithm utilizes the random walk and delete-then-insert operator as a local search method and multi-mode forward–backward improvement; to improve the exploitation ability of the proposed algorithm search space. The proposed algorithm showed better results when compared with the standard EDA [192].

VII. DISCUSSION AND LIMITATIONS

In this section, various classifications, discussions and limitations for applications of CI techniques for solving RCPSP are introduced. These classifications are based on different criteria including CI techniques, publication years and numbers, and type of RCPSP as single objective optimization model as well as multiobjective model over the last five years as shown in Figs. 1-6. Firstly, a classification based on publication years and numbers of research work is depicted in Fig.1. The manifest of the great growth in using CI techniques in solving project scheduling problems especially RCPSP and its variants and extensions is shown in Fig.1. Secondly, a classification based on CI approach is shown in Figs. 2 and 3. Obviously, as shown in Fig.2 and Fig.3 the GA(s) has the Lion share in solving RCPSPs, and the next method is ACO, then PSO and finally the applications of ANN in solving RCPSP(s) are quite poor. Besides, it is clear that using new CI techniques, such as memetic algorithm, agent based metaheuristics, multi-agent system, population learning algorithm, artificial immune system and iterative flattening search, are growingly used in solving RCPSP and showing very promising results. Conveniently, from the knowledge in hand it is very clear that hybrid CI techniques showed better results but needs further investigations (see Figs. 2 and 3). But unfortunately, fuzzy RCPSP were considered are very few and needs more consideration and generally models with fuzziness and randomness needs more analysis and investigations.

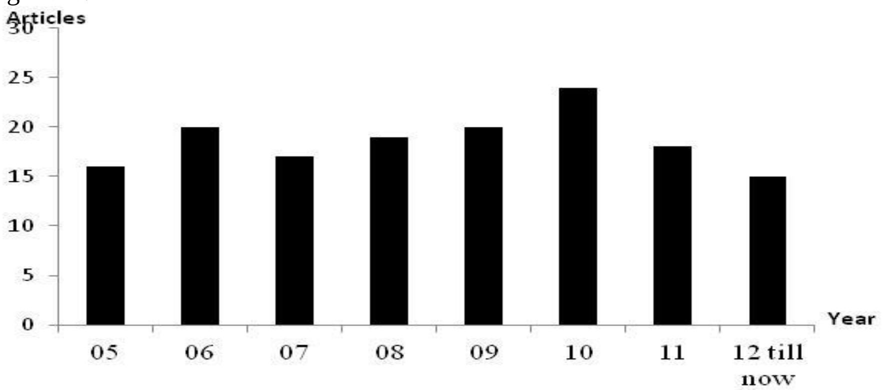

Fig. 1 CI used for RCPSP by years

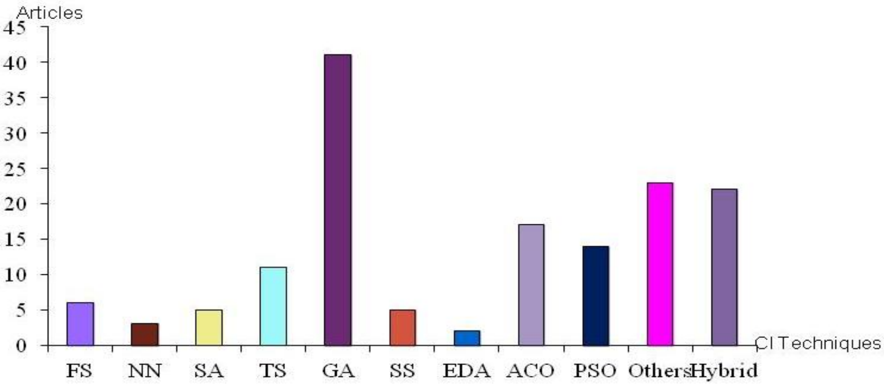

Fig.2 CI paradigms used for RCPSP

Fig.4 shows a classification based on the used RCPSP optimization model. As shown in Fig.4 the great growth of research of using CI techniques to solve RCPSP as single objective optimization model rather than multiobjective optimization model. A classification based on type of objective function as makespan and nonordinary is shown in Fig.5. The last classification considered in this discussion is based on resource types including renewable, nonrenewable resources and doubly constrained are shown in Fig.6.

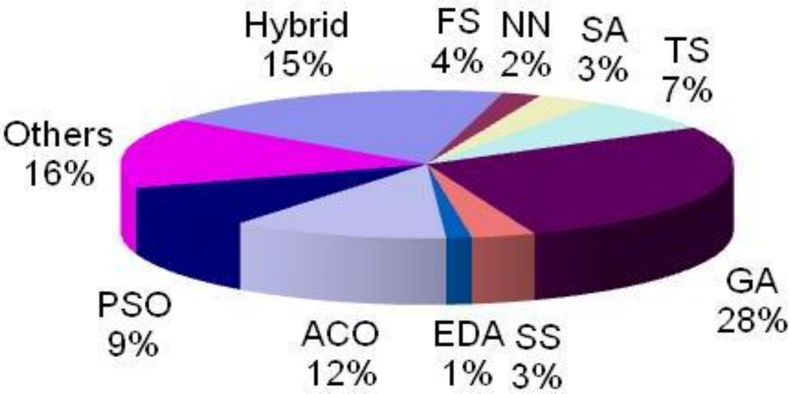

Fig. 3 The usage rate of using CI techniques for RCPSP

Based on above mentioned classification and discussions, there are some limitations in that the RCPSP variants and extensions in this review needs to be considered to model real conditions. There are very few approaches that (heuristically) calculate the efficient set of MORCPSP as shown in Fig.4. Also in introducing nonordinary objective functions instead of minimizing the project makespan (e.g. maximize NPV, project Profit, time lags, resource productivity etc.) are very few as shown in Fig.5. In addition to, handling dynamic resource levels that change over time, resources, i.e., crews, that can share activities, nonrenewable resources, partially locatable resources into more than one activity, resources used at a reduced rate all are issues not considered yet in the literature (see Fig.6). These circumstances must be modeled and accomplished using the activity-based view in CPM scheduling associated with the advancement in CI methods and hybrid methods.

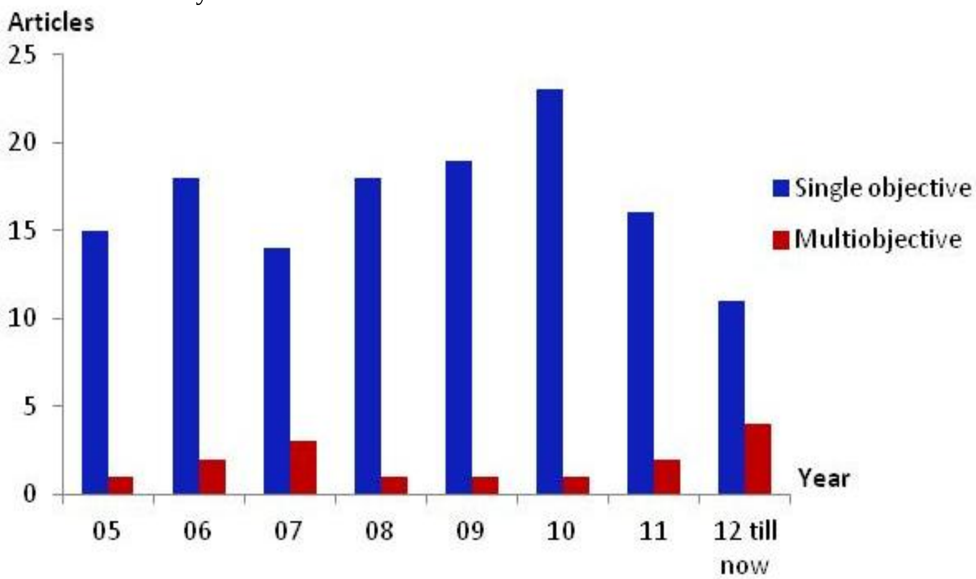

Fig. 4 Single or Multiple objective function used in the model

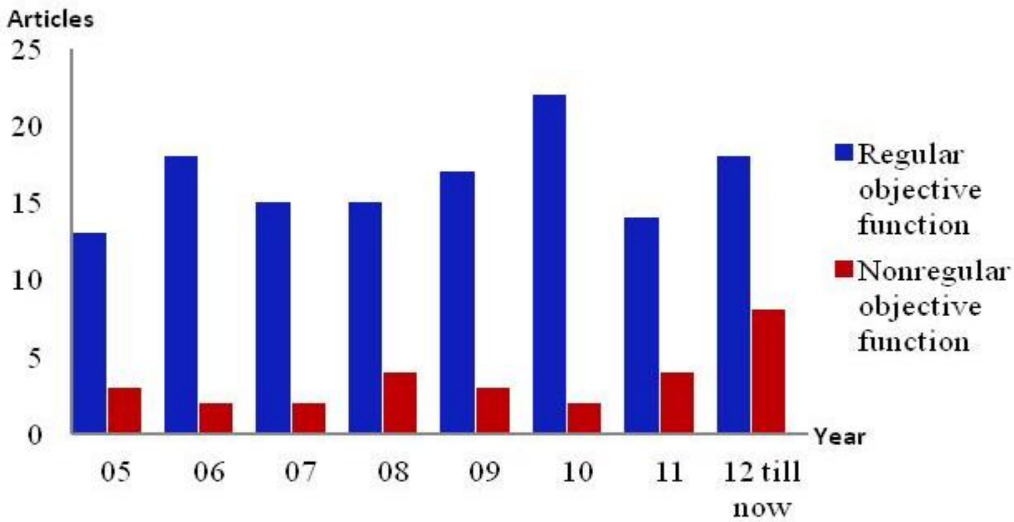

Fig. 5 Type of objective function

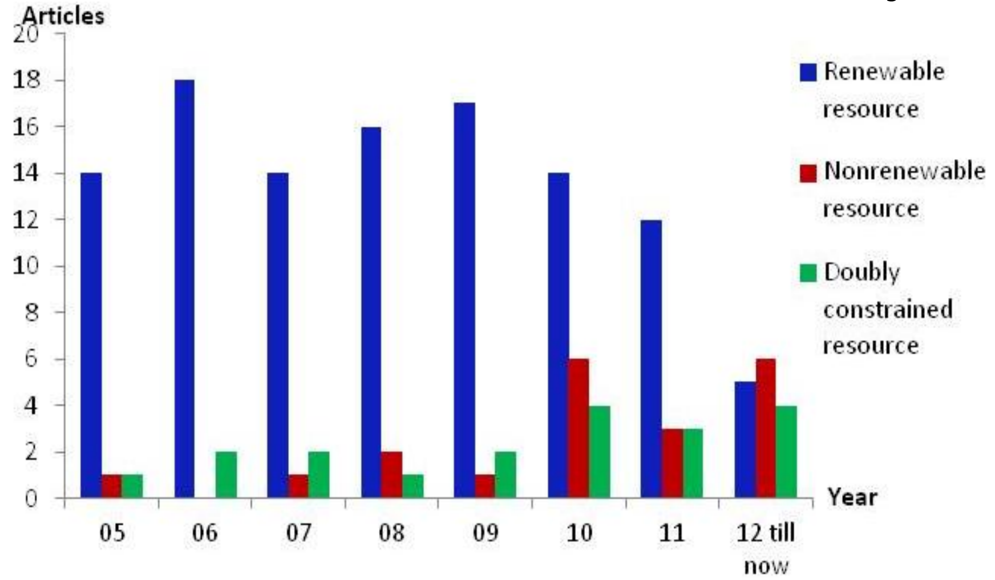

Fig. 6 Type of resources

VIII. CONCLUSIONS AND FURTHER RESEARCH

The main goal of this paper has been to review the results across the use of CI approaches in solving RCPSP which have not been comprehensively discussed yet within a common terminological and methodological framework. An important effect of such a survey is the exposure of problems which are worth to become a subject of future research. Below we present some conclusions and possible directions for future work. As a conclusion in this review, we can see that there are very few approaches that (heuristically) calculate the efficient set of MORCPSP and there are serious doubts that they can truly achieve this. As far as we know, no paper has focused on the theoretical aspects of MORCPSP. This issue needs more effort to be investigated. Moreover, there is a need to make a comment on computational experiments described in the RCPSP and its extensions literature. The current state is that no common standard has been elaborated indicating how computational experiments should be performed, which data sets should be used, which measures should be considered, which other results and how should be used for comparison, etc. Thus, in our opinion, there is a need to establish a set of rules according to which computational experiments should be carried out. This would increase the reliability of the obtained results. A good idea would be to collect all the data sets and data generators used in the literature at one site. The data files should be coded in one standard and extensible format, which does not depend on the software and hardware environment. Moreover, it would also be useful to build a repository of CI algorithms that could be used for comparison with newly developed approaches. Then, these algorithms could be used in computational experiments performed in the same environment.

There are some further research directions and issues in the field of CI and RCPSP should be addressed. These issues include developing more robust parallel search methodologies that could approach to optimal solutions for various RCPSP that have long been intractable; further applications of CI to a more complicated RCPSP with multiple objectives (e.g., leveling of resource usage and minimizing of project duration) and consideration of uncertain activity duration or preemption should be investigated. Another issue is to focus on assessing the extension of potential gains in using the agent-based algorithms and distributed virtual environment using multi agent systems for solving the RCPSP through increasing a number of optimization agents and computation platforms. Also other improvement algorithms and techniques will be tested with a view to finding best combination of agents to deal with particular project scheduling problem types. Also, the work on CI addresses the inclusion of resource-based scheduling techniques to account for AND/OR resource-combination requirements at the network nodes, and ways to generate resource-leveled schedules in agreement with traditional methods. Thus, the research area concerning problems with multiple processing modes and financial objectives seems still to be wide open. The same applies to multi-mode problems with other objectives, e.g. resource-based objectives which have only been tackled in few papers.

In addition to, the possible future works in the field of the preemptive MRCPSP are also worth mentioning. Analyses of the preemptive project scheduling problems under objectives other than minimizing the project makespan are certainly another direction for further research. Finally, the majority of research efforts in project scheduling assume complete information about the scheduling problem to be solved and assume a static deterministic environment. Basically the research efforts aim at the generation of feasible baseline schedules that ’satisfice’ or optimize single or multiple objective functions.

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