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A genetic algorithm-based decomposition approach to solve an integrated equipment-workforce-service planning problem ☆

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ABSTRACT

We develop a new genetic algorithm to solve an integrated Equipment-Workforce-Service Planning problem, which features extremely large scales and complex constraints. Compared with the canonical genetic algorithm, the new algorithm is innovative in four respects: (1) The new algorithm addresses epistasis of genes by decomposing the problem variables into evolutionary variables, which evolve with the genetic operators, and the optimization variables, which are derived by solving corresponding optimization problems. (2) The new algorithm introduces the concept of Capacity Threshold and calculates the Set of Efficient and Valid Equipment Assignments to preclude unpromising solution spaces, which allows the algorithm to search much narrowed but promising solution spaces in a more efficient way. (3) The new algorithm modifies the traditional genetic crossover and mutation operators to incorporate the gene dependency in the evolutionary procedure. (4) The new algorithm proposes a new genetic operator, self-evolution, to simulate the growth procedure of an individual in nature and use it for guided improvements of individuals. The new genetic algorithm design is proven very effective and robust in various numerical tests, compared to the integer programming algorithm and the canonical genetic algorithm. When the integer programming algorithm is unable to solve the large-scale problem instances or cannot provide good solutions in acceptable times, and the canonical genetic algorithm is incapable of handling the complex constraints of these instances, the new genetic algorithm obtains the optimal or close-to-optimal solutions within seconds for instances as large as 84 million integer variables and 82 thousand constraints.

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1. Introduction

In this paper, we study the problem of effectively and efficiently solving an equipment-workforce-service planning (EWSP) problem through an innovatively designed genetic algorithm (GA). The decision problem we solve seeks a minimum-cost solution for decisions of equipment purchasing, human resource recruitment and training, and resource assignment in a multi-type resource (equipment and human resource) and multi-period planning horizon setting. Each of the three types of decisions has been extensively studied in the literature (e.g., [8,9,10,14,18,21,26,35]). However, only a few attempts have been made to bring all these decisions together [6,7], despite the fact that all these decisions are closely related and need to be conducted in a coordinated way. Noticing the gap between theoretical studies and practical requirements, Li et al. [19] proposed an integrated model that applies to the multi-type resource and multi-period planning horizon case and compared the cost savings of the integrated model with other decision models. Their work showed that an integrated model, if effectively solved, can serve as a powerful tool to help service companies reduce costs and improve service operations. Solving the integrated model effectively, however, poses a big challenge.

Because the EWSP problem requires explicit modeling for the match between each type of equipment and each type of worker, the size of the integrated model increases exponentially with the number of equipment types. When the number of equipment types is 12, the number of the integer variables in the model will be around 85 million. On such an extremely large scale, IBM CPLEX either takes a long time to solve or reports out of memory using

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the Integer Programming procedure. In this paper, we propose a GA-based decomposition approach to solve the EWSP decision problem instead. The approach has been shown by various tests to be very effective in finding optimal or close-to-optimal solutions in just a few seconds for instances as large as 84 million integer variables and 82 thousand constraints.

GA is a commonly used modern heuristic algorithm, first introduced by Holland [16] based on an idea derived from the process of biological evolution in nature. A canonical GA [32], or a simple GA as referred to in Goldberg [15], begins with a population of randomly generated chromosomes. An intermediate population is then selected, and recombination and mutation are applied to the intermediate population to create the next population. The canonical GA makes relatively few assumptions about the problem that is being solved and the algorithm framework is generally problem independent [32]. On the other hand, many GA designs face the challenge of how to deal with epistasis of genes, which is problem dependent.

The interaction between different genes in a chromosome is referred to as *epistasis* [3,4]. In the biological sense, a gene is epistatic if its presence suppresses the effect of another gene, which is called *hypostatic*. Epistasis makes problems all-or-nothing tasks and very difficult to solve. There are usually two ways to deal with the epistasis in GA: as a coding problem or as an operator problem of crossover/mutation [3]. In addition, the two approaches can be used simultaneously, as suggested by Davis [11]. Epistasis is also reflected in the complex constraints of decision problems, a well-known difficulty in handling the canonical GA paradigm [1]. Three methods are commonly used to tackle constraints: (1) penalty in fitness functions (e.g., [1]), (2) repair operators (e.g., [5,30,31]), and (3) improved coding/customized crossover (e.g., [33,36]). In our study, we develop a new method to confront the epistasis of problems. Our method decomposes a problem into evolutionary variables and optimization variables. The evolutionary variables are changed by the GA procedure and any values of the evolutionary variables are always feasible for the problem. The values of the optimization variables can be obtained by solving the optimization problems, given the values of the evolutionary variables.

The coding method and the corresponding operators are critical to GAs. Most GAs apply binary coding (e.g., [1,24]), integer coding (e.g., [20,27,34]), or real number coding (e.g., [36]). Similar to Yang et al. [34], our GA also adopts an integer-coded matrix to represent a chromosome. For GA operators, it is often necessary to develop specific genetic operators when using value-encoding methods [28]. Yang et al. [34] suggested block crossover and mutation operators when the chromosome is a matrix, and showed that block-based operators outperform point-based operators. Ruiz et al. [27] used heuristics to initialize the population more efficiently. In our study, we develop more powerful genetic operators and show their superiority to the block-based operators.

Our study is related to the so-called Hybrid Genetic Algorithm (HGA) design, too. HGA, also referred to as *memetic algorithms*, combines random GA operators with local search algorithms. Although some researchers have argued that hybridizing will undermine the schema-processing capabilities of GA, HGAs typically do well in experiments [25]. The GA we design is also hybrid in the sense that we design a new operator, self-evolutions, which incorporates local improvements for each chromosome selected. Different from local search techniques such as neighborhood search [27,29] or hill-climbing [1], however, our local improvement fully utilizes domain knowledge [12] and guarantees improvement if conditions are satisfied. In addition, our algorithm maintains only efficient and valid individuals. Although some studies have pointed out that a bias toward efficient and valid solutions can lead to inferior results (e.g., [22]), our experiments show that this strategy outperforms the alternative that allows inefficient and invalid individuals.

The rest of the paper is organized as follows. Section 2 presents the model formulation and addresses the complexity of the problem. Section 3 gives details about the GA-based solution approach. Section 4 exhibits a series of test results to evaluate the performance of the proposed method. Section 5 concludes the paper.

2. Problem formulation

The EWSP Problem considered in this paper seeks to minimize total costs associated with three planning decisions while satisfying capacity requirements and coordination requirements among the three planning decisions.

2.1. Notations

2.1.1. Sets

T	set of time periods; each period $t \in T$.
I	set of equipment types; each type of equipment $i \in I$.
J	set of worker types; each type of worker $j \in J$.
Ω	set of *feasible* worker training combination $(j,j') \in \Omega$.
Ψ	set of *qualified* equipment-worker match combination $(i,j) \in \Psi$.

Note that a worker type combination (j, j') is *feasible* only if j is less skilful than j' and a worker-equipment type combination (i, j) is *qualified* only if j contains all skills required by i. The construction of set Ω and Ψ precludes infeasible training combinations and unqualified equipment-worker combinations. Thus, the model will not allow infeasible matches such as when a trained worker becomes an untrained one.

2.1.2. Parameters

c_i	capacity of each equipment $i, i \in I$.
d_t	capacity requirement at period t, $t \in T$.
γ	discount factor, $0 < \gamma < 1$.
$l_{jj'}$	training period from worker types j to j', $(j,j') \in \Omega$.

2.1.3. Cost parameters

h_{jt}	Cost of hiring and holding a type j worker from period t; $j \in J$, $t \in T$.
f_{it}	Cost of purchasing and holding a type i equipment from period t; $i \in I$, $t \in T$.
$r_{jj't}$	Cost of training and holding a type j worker to type j' from period t; $(j,j') \in \Omega$, $t \in T$.
m_{ij}	Cost of using a type i equipment and type j worker in service, $(i,j) \in \Psi$.

Note that variables h_{jt}, f_{it}, and $r_{jj't}$ include not only costs incurred at period t but also the total "holding cost" from t to the end of the planning horizon. Specifically, the holding cost of h_{jt} includes the salary paid to a type j worker from period t to the end of the planning horizon, the holding cost of f_{it} includes the maintenance cost spent on one piece of type i equipment from period t to the end of the planning horizon, and the holding cost of $r_{jj't}$ includes the salary difference between a type j worker and a

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