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Merging crow search into ordinal optimization for solving equality constrained simulation optimization problems

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ABSTRACT

Equality-constrained simulation optimization problems (ECSOP) involve the finding of optimal solutions by simulation within a well-defined search space under deterministic equality constraints. ECSOPs belong to the class of NP-hard problems. The large search space makes them difficult to solve in a short period using conventional optimization techniques. An approach that merges the crow search (CS) into ordinal optimization (OO), abbreviated as CSOO, is developed to find a near-optimal solution to the ECSOP within a reasonable time. The proposed approach has three phases, which are surrogate model, exploration and exploitation. First, a surrogate model, based on the multivariate adaptive regression splines, is used to evaluate the fitness of a solution. Next, an enhanced crow search algorithm is used to find N excellent solutions in the search space. Finally, an intensified optimal computing budget allocation is used to find a near-optimal solution among the N excellent solutions. The proposed CSOO approach is applied to a three-stage ten-node network-type production line, and the formulated problem is an ECSOP with a large search space. The developed formulation can be used for network-type production lines with any distribution of arrivals and production times. Simulation results that are obtained using the CSOO are compared with those obtained using four competing methods Test results reveal that the proposed approach yields a near-optimal solution of much higher quality than obtained using four competing methods, and with a much higher computing efficiency.

1. Introduction

Equality-constrained simulation optimization problems (ECSOP) involve the finding of optimal solutions by simulation within a well-defined search space under deterministic equality constraints [1–3]. The ECSOP is solved by simulations, using simply a computer-based mathematical model or a real-world complex calculation of a physical system [4]. The goal of the ECSOP is to find the optimal settings of a physical system that optimize its performance under deterministic equality constraints. An ECSOP is an NP-hard problem [5]; the class of such problems is a special class of optimization problems for most of which probably no polynomial-time search methods exist. In practice, the large search space makes finding an optimal solution by conventional optimization within a short period very difficult.

Various methods had been developed for solving NP-hard optimization problems including, for example, gradient search methods [6] and heuristic methods [7]. Gradient search methods [6], such as the steepest descent method and the conjugate gradient method, may become trapped at a local minimum and converge very slowly. Heuristic methods [7] such as simulated annealing (SA), Tabu search (TS), evolutionary algorithms (EA) [8] and swarm intelligence (SI) [9] are used to find global optimal solutions. However, the quality of the solutions that are found by SA and TS depend strongly on fine parameter tuning. EA [8] are stochastic search methods based on natural biological evolution, and apply the principle of "survival of the fittest" to yield successively better approximations to an optimal solution. EAs are of three basic types – genetic algorithms (GA), evolution strategies (ES), and evolutionary programming (EP). Although some EP algorithms can be proved to converge asymptotically based on the A* accessibility-type assumption [10], the accuracy of a solution that is obtained in a limited computational time cannot be guaranteed in most instances of EA.

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SI [9] is the intelligent behavior that emerges from the collective behavior of many autonomous agents with a common group objective, and is observed in natural systems such as flocks of birds, schools of fish, and colonies of ants or bees. Some popular SI techniques include particle swarm optimization (PSO), artificial bee colony (ABC), ant colony optimization (ACO), social cognitive optimization (SCO), harmony search (HS), the bat algorithm (BA), and the crow search algorithm (CSA) [11,12]. Among them, Sun et al. proved the global convergence of the improved SCO [13]. Furthermore, the stochastic PSO is guaranteed to convergence to the global optimization solution with probability one [14]. Most of these SI techniques require only objective values and achieve a balance between exploration and exploitation. Although existing SI methods have some successful applications [15], numerous significant technical hurdles and barriers are yet to be overcome [16].

An ECSOP is difficult to solve because (i) evaluation of the performance is time-consuming; (ii) the search space is large; and (iii) all deterministic equality constraints must be satisfied simultaneously. The goal of this work is to solve ECSOPs effectively and efficiently. To resolve issues (i) to (iii) simultaneously, the ordinal optimization (OO) theory [17] is used to find a near-optimal solution quickly. OO supplements existing optimization approaches, but is not itself an optimization method. OO theory resolves the computational difficulty of system optimization by considering order rather than value, and guaranteeing that the solution is good enough rather than the best with high probability. The first step in OO is to evaluate all solutions rapidly using a crude evaluation to generate a selected subset. A crude evaluation tolerates large modeling noise. OO theory states that the order of solutions is probably maintained when they are crudely evaluated, and the soundness of order preservation is more closely related to evaluating accuracy [17]. Next, a candidate subset is chosen from the selected subset. Finally, solutions in the candidate subset are evaluated by an accurate evaluation, and the one with the best system performance is the required good enough solution. An accurate evaluation yields accurate estimates of system performance. The OO theory has been extensively employed to solve many NP-hard optimization problems, including those related to the hotel booking limits [18], stochastic economic lot scheduling [19], and assemble-to-order systems [20].

To reduce the computing time required to solve an ECSOP, an approach that merges crow search (CS) [11] into ordinal optimization (OO) [17], abbreviated to CSOO, is developed to find a near-optimal solution in a short period. The CSOO approach has three phases, which are surrogate model, exploration and exploitation. First, a surrogate model that is based on the multivariate adaptive regression splines (MARS) [21] is utilized to evaluate the fitness of a solution. Next, an enhanced crow search algorithm (ECSA) is used to determine N excellent solutions from the entire search space. Finally, intensified optimal computing budget allocation (IOCBA) is used to find a near-optimal solution among the N excellent solutions. These three phases dramatically reduce the required computational cost of solving an ECSOP.

The proposed CSOO is applied to solve the buffer resource allocation problems (BRAP) of network-type production lines in automated manufacturing systems (AMS). The purpose of the BRAP is to allocate limited resources efficiently and meet desired objectives effectively under deterministic equality constraints. The BRAP of a network-type production line is formulated as an ECSOP that has a large search space. The *first* contribution of this work is the development of a CSOO approach to find a near-optimal solution to an ECSOP with a lack of structural information within a reasonable computing time. The *second* contribution is the application of the developed approach to maximize the throughput of the network-type production lines.

The remainder of this paper is structured as follows. Section 2 presents the proposed CSOO to determine a near-optimal solution of the ECSOP. Section 3 describes a three-stage ten-node network-type production line which is formulated as an ECSOP and employs the proposed CSOO to this ECSOP. Section 4 demonstrates the test results and compares the results with those obtained by four competing methods. Finally, Section 5 makes conclusions.

2. Merging crow search into ordinal optimization

2.1. Problem statement

The formulation of the considered ECSOP can be described as follows

$$\max\ E[f(\mathbf{x})] \tag{1}$$

$$\text{subject to}\quad g_j(\mathbf{x})=d_j,\quad j=1,\ldots,m. \tag{2}$$

$$\mathbf{L} \le \mathbf{x} \le \mathbf{U}. \tag{3}$$

where $\mathbf{x}=[x_1,\ldots,x_n]^T$ is an n-dimensional solution vector, $\mathbf{L}=[L_1,\ldots,L_n]^T$ is the lower bound, $\mathbf{U}=[U_1,\ldots,U_n]^T$ is the upper bound, $f(\mathbf{x})$ represents the objective function, $E[f(\mathbf{x})]$ denotes the expected objective value, $g_j(\mathbf{x})$ denotes the jth deterministic equality constraint, m represents the number of deterministic equality constraints, and the search space is defined by the bounds. Multiple simulation runs are conducted to estimate accurately the expected objective value. However, performing an infinitely long running simulation is impossible. The standard approach is to approximate the expected objective value by the sample mean, which is defined as follows.

$$\bar{f}(\mathbf{x})=\frac{1}{T}\sum_{t=1}^{T}f_t(\mathbf{x}) \tag{4}$$

where T denotes the total number of simulation runs, $f_t(\mathbf{x})$ is the objective value of the tth simulation run. The value of $\bar{f}(\mathbf{x})$ is an approximation to $E[f(\mathbf{x})]$, and $\bar{f}(\mathbf{x})$ becomes a better estimate of $E[f(\mathbf{x})]$ as T increases. Since the deterministic equality constraints are soft, a quadratic penalty function [22] can be used to transform a constrained optimization problem into the following unconstrained one.

$$F(\mathbf{x})=\bar{f}(\mathbf{x})-\frac{\mu}{2}\sum_{j=1}^{m}\left(g_j(\mathbf{x})-d_j\right)^2 \tag{5}$$

where $\mu>0$ is the penalty parameter. Let T_a denote a sufficiently large value of T. In the sequel, the accurate evaluation of (4) is defined as when $T=T_a$. For simplicity, we let $F_a(\mathbf{x})$ represent the objective value of the unconstrained problem (5) for a given $\mathbf{x}$ using accurate evaluation.

In general, the proposed solution method can be used to solve an inequality-constrained simulation optimization problem with deterministic inequality constraints, $g_j(\mathbf{x})\le d_j$, $j=1,\ldots,m$ [23,24]. Similarly, a quadratic penalty function [22] can be used to transform the constrained optimization problem into the following unconstrained one.

$$F(\mathbf{x})=\lambda\times\bar{f}(\mathbf{x})-(1-\lambda)\times\sum_{j=1}^{m}PF_j(\mathbf{x}) \tag{6}$$