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Research paper

# Multi-objective design optimization for a two-stage transmission system under heavy load condition

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ABSTRACT

A gear reducer is of critical importance to the performance of many transmission systems in automotive, marine, and aerospace applications. In the preliminary design phase, the pursuits of minimum volume, maximum surface fatigue life and maximum load capacity essentially becomes a multi-objective optimization problem. In this paper, a novel meta-heuristics algorithm, Crow Search Algorithm (CSA), is extended to a multi-objective decision scenario based on the strategy embedded in the preference-inspired co-evolutionary algorithm using weights (PICEA-w). The proposed algorithm combines the nature of diversity, the rapid convergence of CSA and the efficient adaptive weights from PICEA-w. The genetic operator applied in the original PICEA-w aims to generate the offspring that is replaced by the food survey strategy of CSA with augmented efficiency. A hoisting transmission optimization problem from heavy cable shovel excavator is solved. Comparisons with other methods are provided to illustrate the effectiveness of the proposed optimization algorithm.



## 1. Introduction

A gear reducer that transmits the motor power (i.e. torque and rotational speed) is a critical component in many transmission applications, such as automotive, marine, and aerospace [1,2]. In the conceptual design, gear volume is usually perceived as the only objective for cost reduction [3–5], while other objectives such as the volume of the house, the surface fatigue life, and the load capability, are often ignored. However, the maximization of the surface fatigue life and load capacity is essential to enhancing the service durability and flexibility of a gear reducer. Hence, it is imperative to formulate a multi-objective optimization problem (MOOP) in the gearbox preliminary design, rather than a single objective optimization [6–10].

Methods with respect to the solution of MOOP can be classified into the priori articulation of preference-based method and the posteriori articulation of preference-based method [11–13]. The widely used priori method is the weighted sum

*Abbreviations:* CSA, crow search algorithm; PICEA-w, preference-inspired co-evolutionary algorithm using weights; NSGA-II, non-dominated sorting genetic algorithm; MOEA/D, multi-objective optimization evolutionary algorithm based on decomposition; MOCSA, multi-objective optimization based on crow search algorithm; PICEA-g, preference-inspired co-evolutionary algorithm using goal vectors.

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**Nomenclature**

| | |
|---|---|
| $\mathbf{x}$ | position of a crow |
| $\mathbf{m}$ | memory of a crow's best position |
| $r$ | random number ranges from 0 to 1 |
| $fl$ | flight length of a crow |
| $AP$ | awareness probability of a crow |
| $AF$ | outline archive |
| $A$ | archive size |
| $p_1$, $p_2$, $w_1$, $w_2$ | pinions and wheels of two-stage transmission system |
| $V^c$ | clearance volume (mm) |
| $d^n$ | out diameter of the boss |
| $d^p$ | drill hole diameter |
| $d^v$ | inside diameter of rim |
| $c$ | thickness of web |
| $SF$ | squared value of the surface fatigue life factor $C_l$ |
| $T$ | load capacity |

method. With particular weights being assigned to different objectives, the original MOOP is converted into a single objective optimization problem (SOOP) which is solved by many optimization algorithms. For the posteriori method, firstly, a partial set of diverse solutions along the Pareto front are generated; then a higher level decision making process is carried out to select one particular solution. Though the prioritization method involves subjective judgment, the posteriori method would provide possible solutions that are more reliable. This is particularly true when sufficient knowledge of the order of objectives is available at the beginning.

Referring to the posteriori preference based method, evolutionary algorithms (EAs) outperform conventional mathematic programming methods due to the nature of population selection [13,14]. A set of solutions can be obtained in each iteration which gives rise to a boost in the computational efficiency. Furthermore, EAs often show great advantage in handling nonconvex or disconnected problems. MOOP algorithms incorporated with EAs can be classified into Pareto-based, decomposition-based and indicator-based methods [15–17]. The basic idea of Pareto-based approach is the construction of a non-dominated solution set, among which the popular one is the sorting method like NSGA-II [18], and its extensions or modifications [19,20]. The decomposition-based approach assigns different sets of weights to the objectives to obtain a set of single objective functions. Then the approximation Pareto optimal front is obtained by solving the aforementioned SOOP collaboratively [21]. The indicator-based approach resorts to a metric, such as hypervolume [22], to select offspring. Recently, decomposition-based methods are shown to be superior to the Pareto-based methods [23], while the indicator-based methods generally accompanies with high computational cost.

In this paper, we extend the bare bones single objective Crow Search Algorithm (CSA) to a multi-objective decision with the decomposition method and apply it to a practical engineering design. The remaining paper is organized as follows. In Section 2, a brief introduction of the bare bones CSA is presented. Section 3 introduces an efficient PICEA-w strategy that is integrated with CSA to formulate an efficient Multi-Objective Crow Search Algorithm, namely MOCSA. Section 4 elaborates on the formulation of practical engineering MOOP. In Section 5, the implementation of the practical MOOP is carried out with the aforementioned algorithm and a comparison between the original design and the new solution is made. In Section 6, the performance MOCSA is assessed with the comparisons of other methods. Section 7 concludes the paper.

## 2. Crow search algorithm

Crow Search algorithm (CSA) was first proposed by Askarzadeh to solve the complex objective function with highly nonlinear and multimodal characteristics efficiently [24]. Inspired by one of the most intelligent colonial organism, crows, the population-based CSA was formulated based on the intelligent behaviors of crows (e.g. face recognition, use of tools, sophisticated communication, caching and retrieving food) [24].

The basic notion of CSA is

(1) Crows live in a flock analogical to the bird flocking and fish schooling inspired swarm particle optimization (PSO) [25],
(2) Crows can recognize the locations they hide food,
(3) Crows follow each other to steal other's food,
(4) Crows prevent their own food from being stolen.

At each iteration $iter = 1, 2, \ldots, iter_{\max}$ (time), a crow has a memory $\mathbf{m}_i^{iter}, i = 1, 2, \ldots, N$ of its own hidden location (i.e. the best food source the crow found till the specific $iter$) in the $D$-dimensional search space (living environment). And the current position of each crow is expressed as $\mathbf{x}_i^{iter} = [x_{i,1}^{iter}, x_{i,2}^{iter}, \ldots, x_{i,d}^{iter}]$. Each memory updates during the iteration, and it corresponds to the best location obtained till now. Assuming in a particular iteration $iter$, crow $j$ intends to visit, meanwhile