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A hybrid group leader algorithm for green material selection with energy consideration in product design

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ABSTRACT

Green material selection with energy-consideration (GMS-EC) in product design is a key issue for realizing green and sustainable manufacturing. In this paper, a comprehensive optimization model for GMS-EC is established. A hybrid optimizing method named chaos quantum group leader algorithm (CQGLA) is designed to obtain the optimal energy-consumption solution in designing products with various complexity. Compared with genetic algorithm (GA), group leader algorithm (GLA) and artificial bee colony algorithm (ABCA), it is observed that CQGLA can perform better in terms of speed, search capability and solution quality.

1. Introduction

Green material selection (GMS) in product design is to select suitable materials for a product to minimize environmental impacts while satisfying other constraints. GMS is especially crucial for energy conservation. Not only during raw material processing, GMS also has great influence on energy consumption during all the life cycle phases since different materials would have different processing methods, recycling strategies, etc. According to [1], the discrepancy of energy consumption using different materials in body-in-white design can be up to 20%. There are two stages for the development of methods for GMS. In the first stage, material property charts are commonly used to select the material by comparing its engineering properties [2]. This method is based largely on the experience of designers, knowing in advance a particular material to be used [3]. However, as product diversity and the number of available material types increase, it becomes tedious to search for the final selection. In the second stage, a decision matrix is applied for its fast and accurate analysis. Weighting coefficients are used to account for the quantitative and qualitative criteria in supporting decision-making [4]. However, these methods are usually applied at the component level and are more suitable for a single component [5].

In pursuance of light weight, increased performance and functionality, products with multi-material and hybrid structures are preferred [6]. Therefore, the assembly and disassembly processes of connected components, which are affected by the material properties, should also be considered. GMS solution must satisfy constraints of product costs, connectivity, functions and quality, and other requirements to be evaluated as a whole. These factors necessitate the search for a more intelligent algorithm for identifying optimal material combination solutions for product design with multi-material components.

In this paper, a comprehensive model utilizing the chaos quantum group leader algorithm (CQGLA) is proposed for green material selection with energy consideration (GMS-EC), in arriving at an optimal solution. The results of a case study show a good improvement in energy conservation.

2. Issues to be considered

2.1. The objective and constraints of GMS-EC

Nomenclature:

i,j	Index of components
k,l	Index of candidate materials
s	Index of life cycle phases in component layer
n_i	Number of candidate materials of ith component
m	Number of components
C_i	ith component of the product
M_{ik}	kth candidate material for ith component
$TCEC$	Total energy consumption in the component layer
SEC	The energy consumption in the subassembly layer
PEC	Product life cycle energy consumption
cec_{ik}	Component layer energy consumption of ith component made of M_{ik}
ec_{iks}	Energy consumption of C_i made of kth material in sth phases in the component layer
$aec_{ik,jl}$	Assembly energy consumption of C_i made of kth material and C_j made of lth material
$dec_{ik,jl}$	Disassembly energy consumption of C_i made of kth material and C_j made of lth material

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C_{Tot} Product life cycle cost
C_U Upper limit of cost
Q_{Tot} Quality value of the product
Q_L Basic value of the qualified product
$\vartheta(i,j)$ If C_i is connected to C_j, then $\vartheta(i,j) = 1$; otherwise $\vartheta(i,j) = 0$.
$\partial(ik,jl)$ If the material selection for C_i and C_j made of lth material is conflicting, then $\partial(ik,jl) = 1$, otherwise $\partial(ik,jl) = 0$.
$\delta(i,k)$ If the kth candidate material is selected for C_i, then $\delta(i,k) = 1$, otherwise $\delta(i,k) = 0$.

Product specification translates consumer needs into manufacturing requirements. Once the material selection in a product design has been completed, many subsequent processes are largely determined. GMS in product design is therefore an important stage in sustainable manufacturing. The requirements of material selection can be classified into three categories:

Environment requirements. The benefit of GMS is primarily reflected in the environmental impacts. Industry consumes some 51% of the world's total energy usage and this has received increasing attention worldwide [7]. Therefore, energy consumption in industry is used as a specific indicator of the environmental impact in the following formulations. Other environmental indicators (e.g., toxic gases emission, CO_2 emission) are used as filtering conditions in screening of the candidate materials.

Cost requirements. In order to maintain their competitiveness, companies are forced to manufacture products with lower costs [8].

Quality requirements. Quality determines the level of acceptance of products in the market. Good quality refers to high functionality, reliability and safety. High product quality can also establish a good brand reputation.

However, these criteria are often conflicting [4]. The task of GMS is to identify an optimal trade-off of these criteria. In order to highlight the issue of energy consumption, the cost and quality are used as the constraints. The importance of cost and quality can be addressed by improving the values of C_U and Q_L. Therefore, the GMS problem considered in this paper is to minimize the entire *PEC* as denoted in the single objective function (1), while satisfying the constraints (2) and (3).

Objective:

$$\text{Min } PEC \tag{1}$$

Constraints:

$$C_{Tot} < C_U \tag{2}$$

$$Q_{Tot} > Q_L \tag{3}$$

The value of Q_{Tot} and C_{Tot} can be calculated using the method proposed in [4] and [9], respectively.

2.2. Two-layer model for life cycle analysis (LCA)

GMS spans the entire life cycle of a product. The entire product life cycle includes several phases: *extraction of material*, *transportation*, *manufacturing*, *assembly*, *usage*, *disassembly* and *recycle/reuse* [10]. However, existing GMS studies mostly consider the manufacturing phase, and with less attention to the other phases which play important role in energy conservation, such as recycle, reuse, etc. [11]. Furthermore, current LCA tools are mostly deployed at the component level where an 'optimal' green material is selected for a single component. The general guideline of such GMS applications is to improve material recyclability as much as possible. However, even if the material selection of each component is optimal, the complete product may be difficult to disassemble for recycling and reuse. Furthermore, the material selection of two connected components could be in conflict, e.g., the relative hardness of two assembled components. GMS of products should be evaluated on the basis of reducing such conflicts as much as possible. Therefore, the material selection solutions should satisfy the constraint illustrated in Eq. (4).

In order to address the above issues, a two-layer GMS model is established and each layer consists of certain life cycle phases. One is the component layer which includes *extraction of materials*, *transportation*, *manufacturing*, *recycle/reuse*. The value of cec_{ik} can be calculated according to Eq. (5). The value of *TCEC* is the sum of cec_{ik} of m components. The other is the subassembly layer which consists primarily of *assembly* and *disassembly* of products. The value of *SEC* can be calculated according to Eq. (6). The usage phase is not considered in this model. The value of *PEC* is the sum of *TCEC* and *SEC* according to Eq. (7).

$$\forall i \in [1,m], j \in [1,m], \quad \text{if } \vartheta(i,j) = 1, \ \delta(i,k) = 1, \ \delta(j,l) = 1, \quad \text{then } (ik,jl) = 0 \tag{4}$$

$$cec_{ik} = \sum\nolimits_{s=1}^{4} ec_{iks} \tag{5}$$

$$SEC = \frac{\left(\sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{n_i}\sum_{l=1}^{n_j}(aec_{ik,jl} + dec_{ik,jl}) \times \vartheta(i,j) \times \delta(i,k) \times \delta(j,l)\right)}{2} \tag{6}$$

$$PEC = \sum_{i=1}^{m}\sum_{k=1}^{n_i} cec_{ik} \times \delta(i,k) + SEC \tag{7}$$

3. Chaos quantum group leader algorithm (CQGLA) for addressing GMS-EC

3.1. A brief introduction of the CQGLA

The group leader algorithm (GLA) is a swarm intelligence algorithm simulating human social behaviour [12]. A complete society can be seen as a combination of several groups consisting of a number of individuals. Each individual represents a solution to the problem. According to the fitness, the individuals in a group can be classified into two types: *leader* and *member*. Utilizing the *recombination operator* and the *one-way crossover operator*, the leader and members can evolve towards better fitness. Compared with other evolutionary algorithms, GLA requires less computation time and has fast convergence speed because of its parallel structure. As there are many possible candidate materials for each component, the solution space of GMS-EC is relatively large. In order to reduce the population scale and improve the convergence of the algorithm, a novel algorithm named chaos quantum group leader algorithm (CQGLA) is developed by introducing the concept of chaotic variable, quantum bit encoding method, and the *quantum rotation operator* of the quantum algorithm (QA) [13].

3.2. CQGLA for addressing the GMS-EC

3.2.1. Structure of CQGLA for GMS-EC

The structure of the proposed COQLGA is shown in Fig. 1. After the *initialization* of CQGLA, the *quantum rotation operator* and *recombination operator* are executed for the leader and members, respectively. The criteria of the solution are then evaluated. If the solution obtained satisfies the terminal conditions, stop the algorithm and output the results. Otherwise, determine whether to execute the *chaos regeneration operator* and *one-way crossover operator*. Repeat the above steps until termination.

3.2.2. Initialization and energy evaluation

Let the qth individual in pth group be X_q^p. The X_q^p can be expressed as $\{X_{q,1}^p | X_{q,2}^p | \ldots | X_{q,i}^p | \ldots\}$, where $X_{q,i}^p$ is the ith chaos quantum gene (CQGene) of X_q^p. As denoted in Eq. (8), the chaotic variable is used as the initial state of CQGene for its randomness, ergodicity and sensibility, so the individual with CQGenes can be