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Multidisciplinary design optimization to identify additive manufacturing resources in customized product development

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Abstract

Additive manufacturing (AM) techniques are ideal for producing customized products due to their high design flexibility. Despite the previous studies on specific additive manufactured customized products such as biomedical implants and prostheses, the simultaneous optimization of components, materials, AM processes, and dimensions remains a challenge. Multidisciplinary design optimization (MDO) is a research area of solving complex design problems involving multiple disciplines which usually interact with each other. The objective of this research is to formulate and solve an MDO problem in the development of additive manufactured products customized for various customers in different market segments. Three disciplines, i.e. the customer preference modeling, AM production costing, and structural mechanics are incorporated in the MDO problem. The optimal selections of components, materials, AM processes, and dimensional parameters are searched with the objectives to maximize the functionality utility, match individual customers' personal performance requirements, and minimize the total cost. A multi-objective genetic algorithm with the proposed chromosome encoding pattern is applied to solve the MDO problem. A case study of designing customized trans-tibial prostheses with additive manufactured components is presented to illustrate the proposed MDO method. Clusters of multi-dimensional Pareto-optimal design solutions are obtained from the MDO, showing trade-offs among the objectives. Appropriate design decision can be chosen from the clusters based on the manufacturer's market strategy.

Keywords: Additive manufacturing; Customized products; Multidisciplinary design optimization

1. Introduction

Additive manufacturing (AM) is an emerging advanced manufacturing technique whose working principle relies on the progressive layer-wise material consolidation from the bottom to top [1]. Due to the enhanced design flexibility, AM processes are suitable for producing customized products that need to satisfy the requirements of different individual customers [2]. Previous researches in design for additive manufactured customized products have been studied in literatures. Thompson et al. [3] illustrated a broad range of AM applications in customized products, including medical devices, custom-fit packaging for shipping, and furniture. Personalized surgical guides made by AM techniques were designed to improve accuracy in surgical operations [4]. Additive manufactured functional hearing aids were designed based on the patients' ear shapes, while the color of the ear bud can also be customized to meet the patients' preferences [5]. Petrovic et al. [6] introduced various biomedical implants and prostheses manufactured by AM, while their shapes and mechanical properties could be customized individually for the customers. Oxman [7] applied the method of "variable property prototyping (VPRP)" to design customized protective gloves against carpal tunnel syndrome (CTS). Multiple materials with different stiffness values were distributed on the glove to constrain wrist rotation and allow palm movement at the same time. Ko et al. [8] used the formal modeling method of

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affordance-based finite state automata to represent customer needs, and a conceptual "customized design for additive manufacturing (CDFAM)" process was proposed to describe the relationships between products, customers, and AM processes. Strategies of *mass customization*, such as platform-based product family design methods [9,10], could be applied to additive manufactured products with the objective to save cost by sharing common components (i.e. platforms) in different product variants. The implementation of mass customization in AM was illustrated in [11], where a family of plastic lightweight structures were designed to meet different strength, weight, and cost requirements. In the research of Yao et al. [12], components of a platform-based R/C racing car family were fabricated by a metallic AM process, while the components' geometric design parameters were optimized to improve product performances at delimited costs. However, in the aforementioned studies of additive manufactured customized products, the components, materials, and AM processes were assumed given, while the sizes and shapes were the only design variables. The simultaneous optimization of the selection of components, materials, AM processes, and dimensional parameters remains a challenge, especially for products that need to meet diverse requirements of individual customers.

Multidisciplinary design optimization (MDO) is a research domain of solving complex engineering design problems incorporated with multiple disciplines [13]. Prior to the formulation and solution of MDO problems, multidisciplinary analysis (MDA) is carried out to understand the relationships among design variables and various involved disciplines [14]. The objective functions and/or constraints derived from the MDA are then used to formulate the complete MDO problem [15]. Due to the complex nonlinear, multivariate, and non-differentiable nature of most MDO problems, traditional gradient-based optimization methods are found inefficient. Meanwhile, population-based evolutionary algorithms, such as bio-inspired genetic algorithms (GAs) [16] and differential evolution (DE) [17], can be used to solve MDO problems conveniently. Historically, MDO methodologies were first proposed for the purpose of designing aircraft components [18,19]. Later research has extended the application of MDO into other types of machines, such as wind turbines whose blade and tower sizes were optimized to reduce the cost of generated energy [20]. Not only complicated machinery but also consumer products can benefit from MDO techniques. In [21], the parametric design of the freeform surface of a hammer was calculated by MDO to minimize the volume, surface area, and characteristic distances. However, MDO problems for additive manufactured customized products have not been reported in literature. While part dimensions were optimized in most previous MDO applications, the simultaneous consideration of material and manufacturing process (especially AM) selections as decision variables has rarely been studied. While previous research in MDO has focused mainly on optimizing a single product, in this research, the MDO problem is formulated for a family of customized multiple product variants for various customers. Each product variant has its own design parameters and materials that may be different from the other variants in the family. In the proposed MDO problem, the personal preference of each individual customer is formulated into one of the objective functions. The second type of the objective functions represents the product's functionality. And the third type of the objective functions represents the total cost of producing the entire product family composed of all the product variants. By optimizing the product family instead of a single product, designers would obtain design solutions that are for the benefit of both the customers and the manufacturer.

In this research, the MDO problem for additive manufactured customized products incorporates three disciplines, i.e. the customer preference modeling, AM production costing, and structural mechanics. The components, materials, AM processes, and dimensional parameters are optimized with the objectives to maximize the functionality utility, match individual customers' personal performance requirements, and minimize the total cost. The multi-objective MDO problem is solved by a genetic algorithm with the proposed chromosome encoding pattern. A case study of designing additive manufactured trans-tibial prostheses is conducted to illustrate the proposed method. As the result, multiple clusters of Pareto-optimal design solutions are obtained and displayed in a 3-D plot.

The remaining parts of this paper are organized as follows. The detailed MDO problem formulation and solution are explained in Section 2. The case study is illustrated in Section 3. The summary of this research and recommendation for future work are presented in Section 4.

2. The proposed MDO problem formulation and solution

In this research, the MDO problem for additive manufactured customized products is formulated and solved. Fig. 1 illustrates the overall architecture of the MDO problem which involves multiple design variables, disciplines, design objectives, and constraints. The identification of appropriate components, materials, manufacturing processes, and dimensional parameters significantly influences the product's performances and cost, and hence it needs to be optimized in the product design stage.

The attractiveness of the product to the customer determines the consumer demand and the product's competitiveness in the market. Therefore, the customer preference modeling (Discipline 1) is carried out in the MDO. As shown in Fig. 1, two levels of design objectives can be formulated via customer preference modeling. In the first objective, mass customization is carried out to satisfy the fundamental functionality requirements reflecting the collective needs of customers. In the mass customization, the product is designed with different component configurations and functions in different market niches, while the same configuration and function are shared within the same market niche due to the common preference (or utility) perceived by customers in the market niche. However, although functionality requirements can be shared, different individual customers may have different personal requirements of the product's performances, such as its size, weight, and other specific properties that should comply with the customer's own physical characteristics (e.g. height, age, gender etc.). Therefore, the second design objective stemmed from the

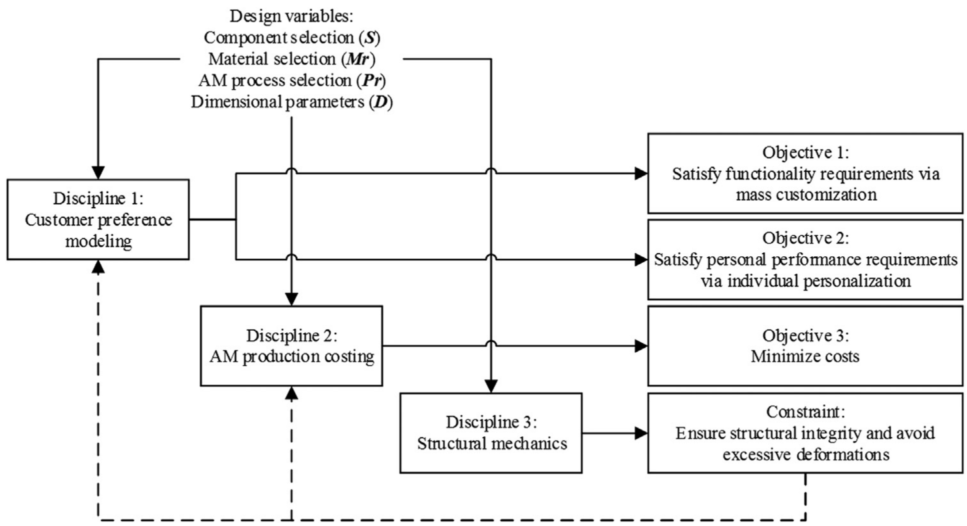

Fig. 1. The overview of the MDO problem.

customer preference modeling is to satisfy personal performance requirements by individually customizing the product design. AM techniques are ideal for fabricating individually customized components due to their superior capabilities to enable high design flexibility at lower costs and shorter lead time than traditional processes [8].

Minimizing costs is another objective in the MDO problem, formulated in Discipline 2 (AM production costing). Given the selected components, materials, processes, and dimensions, we can estimate the AM production cost of the product. As discussed in the previous study [22], although AM enables higher design flexibility than traditional processes, the design customization for different customers may still result in cost increment due to extra resource (e.g. manpower, energy, and materials) consumption.

Analysis in the structural mechanics (Discipline 3) of components is important to ensure structural integrity and avoid excessive deformations. The two dashed arrows in Fig. 1 indicate that the output of the structural mechanics discipline is taken as input to the other two disciplines (i.e. the customer preference modeling and AM production costing) when the three design objectives are evaluated in the MDO.

The remaining parts of Section 2 contain detailed discussions on the specific elements in the MDO problem, including the design variables, three involved disciplines, design constraints, and the population-based optimization solving algorithm.

2.1. Design Variables

As expressed in Eq. (1), component selection ($\boldsymbol{S}$), AM process selection ($\boldsymbol{Pr}$), material selection ($\boldsymbol{Mr}$), and dimensional parameters ($\boldsymbol{D}$) are included in the design variables ($\boldsymbol{X}$) of the MDO for an additive manufactured customized product. $\boldsymbol{S}$ is a vector of binary variables whose values are either 1 or 0 indicating whether or not the corresponding component is selected. $\boldsymbol{Pr}$ and $\boldsymbol{Mr}$ are sets of discrete numbers indicating the collections of available processes and materials. $\boldsymbol{D}$ is a vector of continuous values that represent the physical dimensions.

$$\boldsymbol{X} = [\boldsymbol{S}, \boldsymbol{Mr}, \boldsymbol{Pr}, \boldsymbol{D}] \quad (1)$$

The selection of components determines the fundamental functionalities. In mass customized products, optional or alternative components are made available to customers, so that specific functions can either be added or dropped based on the customers' preferences. Production costs are also influenced by the component selection. Alternative materials may be applied in the same component. The selection of materials significantly affects the mechanical properties, performance, and costs of components. For each selected material, its corresponding AM process also needs to be determined. Different types of AM processes use different energy sources and material bonding/fusing mechanisms, and hence the as-fabricated parts may have different properties and costs even when they are made of the same material. Dimensional parameters of components may be personalized for individual customers based on the measurement and analysis of the customers' physical characters and personal needs. When dimensional parameters are optimized in the MDO, design constraints should be implemented to ensure the AM manufacturability and avoid excessive deformations.

2.2. Incorporation of multiple disciplines

Three disciplines, including 1) customer preference modeling, 2) AM production costing, and 3) structural mechanics, are incorporated in the MDO problem for additive manufactured customized products. Analysis of each discipline and the derived objective/constraint functions are presented in Sections 2.2.1–2.2.3.

2.2.1. Customer preference modeling

Customer preference modeling is carried out in the MDO to evaluate the product's functionalities and performances in terms of customer-perceived utility. The objective functions of satisfying customer needs on both the overall market level and individual customer level are derived in this discipline.

Adapted from marketing sciences, the utility is a term that represents the value of a product perceived by customers [23]. Mathematically, the general expression of the utility is formulated in Eq. (2):

$$U(X) = \beta \cdot A(X) = \sum_{\varphi=1}^{\Phi} \beta_{p_\varphi}[A_\varphi(X)] \tag{2}$$

where $\beta \cdot A(X) = \sum_{\varphi=1}^{\Phi} \beta_{p_\varphi}[A_\varphi(X)]$ is the linear part-worth function. A is the vector of totally Φ key attributes which are functions of the product's design variables X. A_φ is the φth element of A. β is a vector of positive utility weights. As the value of the part-worth function increases, the larger utility is obtained, which may lead to higher customer demand and larger market share.

The first MDO design objective stemmed from customer preference modeling is to satisfy the functionality requirements through maximizing the utility perceived by customers in the overall market collectively. The maximization objective function is shown in Eq. (3):

$$\max : \sum_{i}^{N} U_i^F(S) = \sum_{i}^{N} \left(\beta_i^F \cdot S\right) \tag{3}$$

where $U_i^F(S)$ represents the *functionality utility* in the ith market segment and N is the total number of market segments. The utility U^F is a function of the component selection S that determines whether to enable or disable a particular functionality. Recalling the general expression of utility in Eq. (2), U^F can be modeled by the linear part-worth term $\left(\beta_i^F \cdot S\right)$ where the vector β_i^F contains the positive *functionality utility weights* that can be obtained from market surveys.

AM technologies provide designers with the capability to personalize the product design. Therefore, the second MDO objective is to meet the personal performance requirements specific to individual customers. As shown in Eq. (4), the performance target of a particular customer is expressed as the vector T that contains Φ properties. The performance target is obtained by measuring and analyzing the physical characters of the customer and it is treated as a given constant in the MDO. The performance P is a vector of properties which are functions of materials, processes, and dimensional parameters. The match between the performance and the personal target is expressed as the absolute difference the vectors T and P, as shown in Eq. (5).

$$T = [t_1, t_2, \ldots t_\Phi], P(Mr, Pr, D) = \left[p_1(Mr, Pr, D), p_2(Mr, Pr, D), \ldots p_\Phi(Mr, Pr, D)\right] \tag{4}$$

$$Match(Mr, Pr, D) = \|T - P(Mr, Pr, D)\| \tag{5}$$

Following the general expression of utility in Eq. (2), the objective function of satisfying the personal performance requirements can be written in Eq. (6):

$$\max : \sum_{i}^{N}\sum_{j}^{n_i} U_{ij}^P[-Match(Mr, Pr, D)] = \sum_{i}^{N}\sum_{j}^{n_i} U_{ij}^P[-\|T - P(Mr, Pr, D)\|] = \sum_{i}^{N}\sum_{j}^{n_i}\sum_{i}^{N}\left[\beta_{ij}^P \cdot (-\|T - P(Mr, Pr, D)\|)\right] \tag{6}$$

where U_{ij}^P is the personal *performance utility* to be maximized, β_{ij}^P is the vector containing positive utility weight values, and n_i is the number of customers in the ith market segment. Unlike the positive functionality utility U_i^F, the performance utility U_{ij}^P is always negative. As the performance is made closer to the target, the $Match(Mr, Pr, D)$ term bears a smaller value and hence U_{ij}^P is increased.

2.2.2. AM production costing

In the MDO for additive manufactured customized products, AM production costs are minimized as the third design objective. Given the selected components (S), materials (Mr), AM processes (Pr), and dimensional parameters (D), the total cost (TC) of all customized products can be formulated as:

$$\min : TC(S, Mr, Pr, D) = \sum_{i=1}^{N}\sum_{j=1}^{n_i}\sum_{k=1}^{K}\left[C_k^{Fabricate}(S, Mr, Pr, D) + \Delta C_k^{DesignCust}(D) + \Delta C_k^{ProcessSetup}(Pr)\right] \tag{7}$$

where K is the total number of component in a product; $C_k^{Fabricate}$ is the unit cost of fabricating the kth component; $\Delta C_k^{DesignCust}$ is the *extra* cost incurred from customizing the component design for individual customers; and $\Delta C_k^{ProcessSetup}$ is the *extra* cost of setting up and maintaining multiple different AM processes to produce the same type of component but for different customers. For additive manufactured customized products, the methods of estimating $\Delta C_k^{DesignCust}$ (as a function of dimensional parameters D) and $\Delta C_k^{ProcessSetup}$ (as a function of AM processes Pr) have been presented in the previous research [22,12] respectively. The component fabrication cost $C_k^{Fabricate}$ can be calculated as:

$$C_k^{Fabricate}(S, Mr, Pr, D) = c_m(Mr) \times M_k(S, Mr, Pr, D) + \left[c_{op}(Pr) + c_{manpower}\right] \times \tau(S, Mr, Pr, D) \tag{8}$$

where c_m is the material cost per unit mass, M_k is the net mass of the kth component; c_{op} is machine operation cost per unit time, and $c_{manpower}$ is the manpower cost for monitoring and handle the machine. The total AM processing time τ is affected by the component size and the selected material which determines the printing speed in AM.

2.2.3. Structural mechanics

In the MDO problem, analysis of structural mechanics is carried out to predict deformations in mechanical components under working conditions. Design constraints have to be implemented during the dimensional optimization of components in order to ensure structural integrity and avoid excessive deformations. Finite element models (FEMs) can be used to simulate response forces and displacements at critical locations such as sharp corners, thinnest areas, joints, and contact loading areas etc. However, high-fidelity FEMs are computationally expensive and time-consuming. Therefore, metamodels generated by sampling data obtained from FEMs can be applied to the MDO for improving the solving speed [24]. In this research, artificial neural network (ANN) [25] is used to generate metamodels that take external loadings as inputs and estimate component deformations as outputs. The procedure of applying ANN-based metamodels is illustrated in Fig. 2. A set of design variable sample points ($\boldsymbol{X_S}$) are selected as input to the FEM which generates the simulated output ($\boldsymbol{Y_S}$). In the next step, an ANN metamodel is trained using $\boldsymbol{X_S}$ and $\boldsymbol{Y_S}$ vectors as training data pairs. The trained metamodel is then applied to the MDO solving process whenever the actual design point ($\boldsymbol{X}$) is updated and the output ($\boldsymbol{Y}$) is predicted. The design constraint derived from structural mechanics analysis can be written as:

$$\begin{aligned} &\boldsymbol{\delta_k}(X) = \boldsymbol{MM_k}(X) \le \boldsymbol{\delta_k^{Critical}} \\ &\boldsymbol{MM_k}(X) = \boldsymbol{MM_k}(\boldsymbol{MatP}(\boldsymbol{Mr}, \boldsymbol{Pr}), \boldsymbol{D}) \end{aligned} \tag{9}$$

where $\boldsymbol{\delta_k}(\boldsymbol{X})$ is the predicted deformations in the kth component, ***MM*** represents the metamodel, and ***MatP*** represents the material properties determined by the selected materials and AM processes.

2.3. Bound constraints on dimensions and process selections

AM enables designers to optimize product designs with high flexibility without extra tooling. However, dimensional limitations, such as the maximum height and smallest wall thickness, still exist in the design of components manufactured by a particular AM process. These dimensional limitations are formulated as the inequality constraint functions of the MDO. The general expression is shown in Eq. (10), where the vectors $\boldsymbol{D}^{min}$ and $\boldsymbol{D}^{max}$ are the minimum and maximum allowable dimensional parameters in the AM process ($\boldsymbol{Pr}$) respectively.

$$\begin{aligned} &\boldsymbol{D} \le \boldsymbol{D}^{\max}(\boldsymbol{Pr}) \\ &\boldsymbol{D} \ge \boldsymbol{D}^{\min}(\boldsymbol{Pr}) \end{aligned} \tag{10}$$

Another type of constraint is the limited availability of AM processes that can use a particular material in component fabrication. For example, if ABS, a thermoplastic material with good strength, is chosen, its corresponding AM process selected in the MDO has to be one of the polymer-based AM processes that can handle ABS, while the laser or electron beam powered metallic AM techniques are excluded from the pool of candidates. Mathematically, the process selection constraint can be written in Eq. (11), where the set ***Pr***(***Mr***) matches the available AM processes with the material ***Mr***.

$$\boldsymbol{Pr} \subset \boldsymbol{Pr}(\boldsymbol{Mr}) = [\boldsymbol{Pr_1}, \boldsymbol{Pr_2}, \ldots, \boldsymbol{Pr_Z}] \tag{11}$$

2.4. Solving the MDO problem

Based on the above discussions of design variables, objectives, and constraints, the complete MDO problem for additive manufactured customized products can be formulated as:

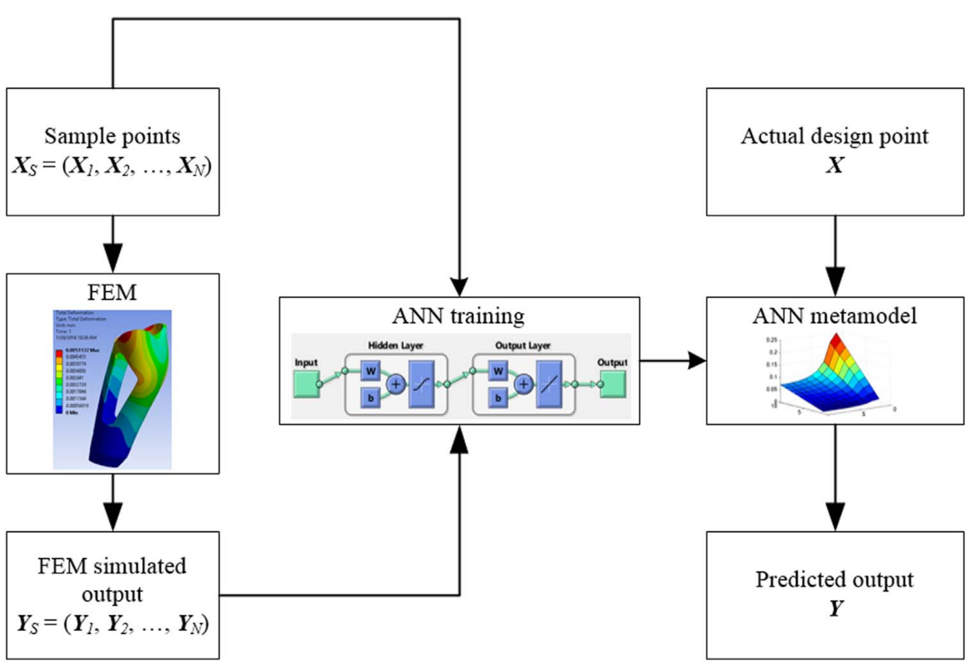

Fig. 2. Incorporation of metamodels in MDO.

$$\text{Design variables}: \boldsymbol{X}_{ij} = [\boldsymbol{S}, \boldsymbol{Mr}, \boldsymbol{Pr}, \boldsymbol{D}]_{ij}$$

$$Objectives: \begin{cases} \max\ : \sum_{i}^{N} U_i^F(\boldsymbol{S}) = \sum_{i}^{N} (\boldsymbol{\beta}_i^F \cdot \boldsymbol{S}) \\ \max\ : \sum_{i}^{N}\sum_{j}^{n_i} U_{ij}^P[-Match(\boldsymbol{Mr}, \boldsymbol{Pr}, \boldsymbol{D})] = \sum_{i}^{N}\sum_{j}^{n_i}\sum_{i}^{N}\left[\boldsymbol{\beta}_{ij}^P \cdot (-\|\boldsymbol{T} - \boldsymbol{P}(\boldsymbol{Mr}, \boldsymbol{Pr}, \boldsymbol{D})\|)\right] \\ \min\ : TC(\boldsymbol{S}, \boldsymbol{Mr}, \boldsymbol{Pr}, \boldsymbol{D}) = \sum_{i=1}^{N}\sum_{j=1}^{n_i}\sum_{k=1}^{K}\left[C_k^{Fabricate}(\boldsymbol{S}, \boldsymbol{Mr}, \boldsymbol{Pr}, \boldsymbol{D}) + \Delta C_k^{DesignCust}(\boldsymbol{D}) + \Delta C_k^{ProcessSetup}(\boldsymbol{Pr})\right] \\ \forall i \in N(\text{market segments}), \forall j \in n_i(\text{individual customers}), \forall k \in K(\text{components}) \end{cases}$$

$$\text{Subject to}: \begin{cases} h1: \boldsymbol{MM}_k(\boldsymbol{MP}(\boldsymbol{Mr}, \boldsymbol{Pr}), \boldsymbol{D}) \le \boldsymbol{\delta}_k^{Critical} \\ h2: \boldsymbol{D} \le \boldsymbol{D}^{\max}(\boldsymbol{Pr}) \\ h2: \boldsymbol{D} \ge \boldsymbol{D}^{\min}(\boldsymbol{Pr}) \\ g1: \boldsymbol{Pr} \subset \boldsymbol{Pr}(\boldsymbol{Mr}) \end{cases} \tag{12}$$

The proposed MDO formulation is a multi-objective, nonlinear, and mix-integer optimization problem that can be solved by population-based evolutionary algorithms [9]. In this research, a non-dominated sorting genetic algorithm (NSGA-II) proposed by Deb et al. [26] is used to solve the MDO problem. NSGA-II has been applied in various research domains. For example, Asadi et al. [25] used NSGA-II to optimize the retrofitting actions for a school building to improve thermal comfort and reduce energy consumption. Wang et al. [27] estimated the greenhouse gas emission and operating cost as functions of a jet aircraft's wing configuration and operational parameters, and optimized the aircraft design using NSGA-II. Kanagarajan et al. [28] optimized the process parameters of electrical discharge machining (EDM) using NSGA-II to maximize the material removal rate and surface finish. The major difference between our implemented NSGA-II and the above mentioned references lies in the chromosome encoding pattern. In this research, a chromosome contains the multiple types of decision variables (e.g. parametric design, materials, and AM process selection) for multiple product variants belonging to the same family, while a chromosome in the previous references represents only a single subject (or product).

The general working principle in genetic algorithms mimics the biological evolution process in nature, in which the chromosomes are modified by crossovers and mutations across generations and those with advantageous genes are preserved by natural selection. In the NSGA-II, the string of chromosome contains design variables of additive manufactured customized products for all customers. In this research, the proposed chromosome encoding pattern is in shown in Fig. 3, where each variable resembles a gene that undergoes evolution in the MDO.

The MDO solving procedure based on the NSGA-II is illustrated in Fig. 4. The initial population of chromosomes is assigned with random values. In each iteration, three objective functions are evaluated and the Pareto-optimal chromosomes are searched by non-dominated sorting. Crowding distance sorting is also carried out to preserve the diversity of genes across chromosomes during the convergence. Crossover and mutation operations are used to update the chromosome population [26]. When the same design variables affect different objectives simultaneously, trade-offs may exist among these objectives. Therefore, in the proposed MDO problem, we do not aim to identify a singular global optimal design solution. Instead, a collection of multiple non-dominating Pareto optimal solutions

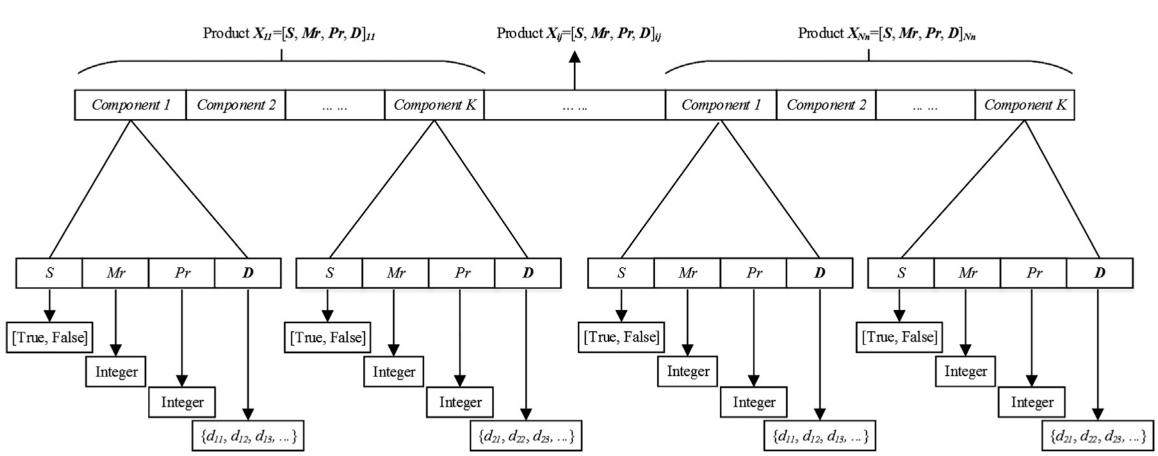

Fig. 3. The chromosome encoding pattern in NSGA-II.

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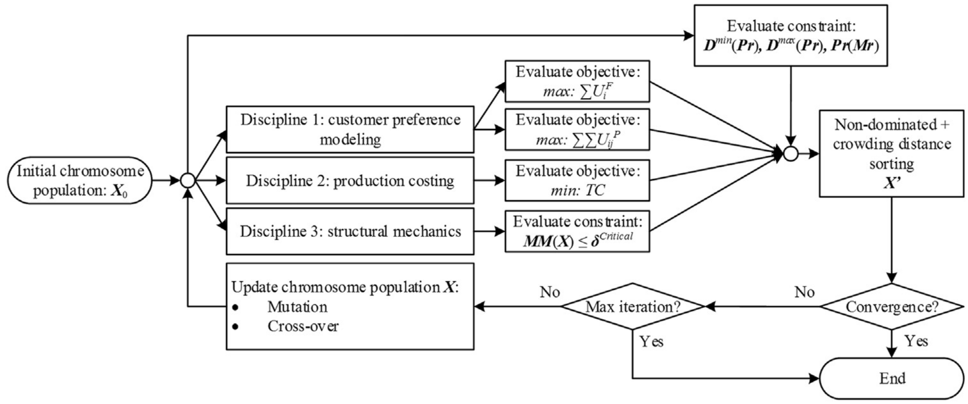

Fig. 4. The MDO solving procedure based on NSGA-II.

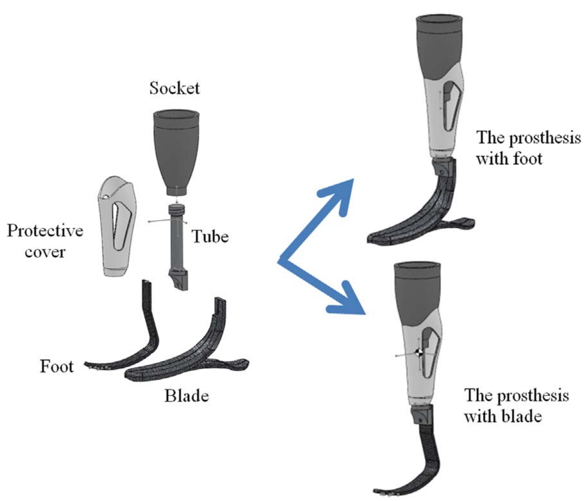

Fig. 5. Trans-tibial prosthesis components.

will be obtained. In this research, the final solution of the MDO is a three-dimensional Pareto surface that can be visualized in a 3-D plot. By observing the 3-D plot, designers can compare the resultant product performances and costs in different Pareto-optimal designs, from which designers can select the preferred solution based on the companies' marketing strategies.

3. Case study

The proposed MDO method is illustrated in the case study of designing customized trans-tibial (TT) prostheses. As reported in [6], AM techniques are ideal for TT prosthesis fabrication due to their better flexibility and shorter lead time compared with traditional methods which require a lot of mold making work. In the MDO for additive manufactured TT prostheses, the objectives are to 1) fulfill basic functional requirements of TT prostheses in different market segments by selecting appropriate components, 2) match the personal performance targets of individual customers based on their weights, leg lengths, and foot sizes, and 3) save the total cost as the result of customizing and producing all the TT prostheses.

The components of the TT prosthesis are shown in Fig. 5 with both the exploded view and assembled view. The tube is a standard off-the-shelf component that is implemented in all prostheses, and hence its design is assumed constant and not involved in the MDO. The socket, protective cover, foot, and blade are customizable components whose materials, processes, and dimensions can be optimized by solving the MDO. The design variables and the available material/process candidates for each component are listed in Table 1. Since the socket ($k=1$) must be implemented in all prosthesis designs, the corresponding component selection variable is always the constant ($S_1 \equiv True$). Meanwhile, the foot ($k=2$), blade ($k=3$), and protective cover ($k=4$) are considered the "optional components". Whether or not the optional components are implemented depends on the value of S_k calculated from the MDO. In addition, either the foot or blade (but not both) must be selected, and hence their corresponding component selection variables must satisfy the relationship:

$$\begin{aligned} \boldsymbol{S_2} \cup \boldsymbol{S_3} &= \boldsymbol{True} \\ \boldsymbol{S_2} \cap \boldsymbol{S_3} &= \boldsymbol{False} \end{aligned} \tag{13}$$

Two major market segments, i.e. "Casual Users" and "Sporty Users", are identified among TT prosthesis customers. The part-worth utility weights of the optional components are listed in Table 2.

TT prostheses are customized for four individual customers, two in each market segment. For simplicity, in this case study, the personal performance targets concerns only the sizes and weights of the TT prosthesis components, as shown in Table 3 where C_{ij} represents the jth individual customer in the ith market segment. More complicated measurements of performance targets, such as the aesthetic appealing felt or needed by customers, may be taken into consideration in future work.

For each of the material candidates, there is a limited pool of applicable AM processes ($\boldsymbol{Pr}(\boldsymbol{Mr})$) that can be chosen from during the design optimization. The match between materials and AM processes are shown in Table 4. Although the lists presented in Table 4 are not exhaustive, they represent the major categories of commonly used material and AM processes in the industry, and hence they are considered sufficient in this case study for illustration purpose.

Deformation constraints ($\delta_k^{critical}$) of TT prosthesis components are listed in Table 5. The motion of a customer wearing the prosthesis can be simulated in the software OpenSim [29], as shown in Fig. 6. Reaction forces and deformations of the TT

Table 1
Design variables of TT prostheses.

No. *(k)*	Design variables			
	Component selection (S_k)	**Materials (Mr_k)**	**AM Processes (Pr_k)**	**Dimensions (D_k)**
1	Socket ($S_1 \equiv True$)	• ABS • PP • Rubber	• FDM (Stratasys Dimension Elite) • SLA (Stratasys Objet500)	• Diameter • Length • Thickness
2	Foot	• ABS • PP • SS316L • AlSi10Mg • Ti6Al4V • CoCr	• FDM (Stratasys Dimension Elite) • SLA (Stratasys Objet500) • SLM (SLM Solutions SLM250HL) • EBM (Arcam A2XX)	• Length • Width • Thickness
3	Blade	• ABS • PP • SS316L • AlSi10Mg • Ti6Al4V • CoCr	• FDM (Stratasys Dimension Elite) • SLA (Stratasys Objet500) • SLM (SLM Solutions SLM250HL) • EBM (Arcam A2XX)	• Length • Width • Thickness
4	Protective cover	• ABS • PP • Rubber • AlSi10Mg • CoCr	• FDM (Stratasys Dimension Elite) • SLA (Stratasys Objet500) • SLM (SLM Solutions SLM250HL) • EBM (Arcam A2XX)	• Length • Width • Thickness

Table 2
Part-worth utility weights of the optional components.

Optional component	Market segments (*i*)	
	1 ("Casual Users")	**2 ("Sporty Users")**
Foot	0.6	0.1
Blade	0.2	0.7
Protective cover	0.2	0.2

Table 3
Personal performance targets of four individual customers.

Components (*k*)	Properties targets	Market segments (*i*)			
		1 ("Casual Users")		**2 ("Sporty Users")**	
		C_{11}	C_{12}	C_{21}	C_{22}
Socket	Diameter (mm)	110	122	135	146
Protective cover	Length (mm)	280	350	410	490
	Weight (kg)	1.30	1.41	1.47	1.52
Foot	Length (mm)	210	230	240	260
	Weight (kg)	0.65	0.70	0.80	0.90
Blade	Length (mm)	200	215	226	242
	Weight (kg)	0.56	0.60	0.70	0.83

Table 4
The available AM processes for each material candidate.

Material (Mr_k)	AM process (Pr_k)
ABS	FDM (Stratasys dimension elite) SLA (Stratasys objet500)
PP	SLA (Stratasys objet500)
Rubber	SLA (Stratasys objet500)
SS316L	EBM (Arcam A2XX) SLM (SLM solutions SLM250HL)
AlSi10Mg	SLM (SLM solutions SLM250HL
Ti6Al4V	EBM (Arcam A2XX) SLM (SLM solutions SLM250HL
CoCr	EBM (Arcam A2XX) SLM (SLM solutions SLM250HL

Table 5
Deformation constraints.

Component (*k*)	Deformation constraints ($\delta_k^{critical}$)	Values
Protective cover	Maximum bending deflection (mm)	5
Foot	Maximum heel deflection (mm)	15
	Maximum toe deflection (mm)	12
Blade	Maximum toe deflection (mm)	10

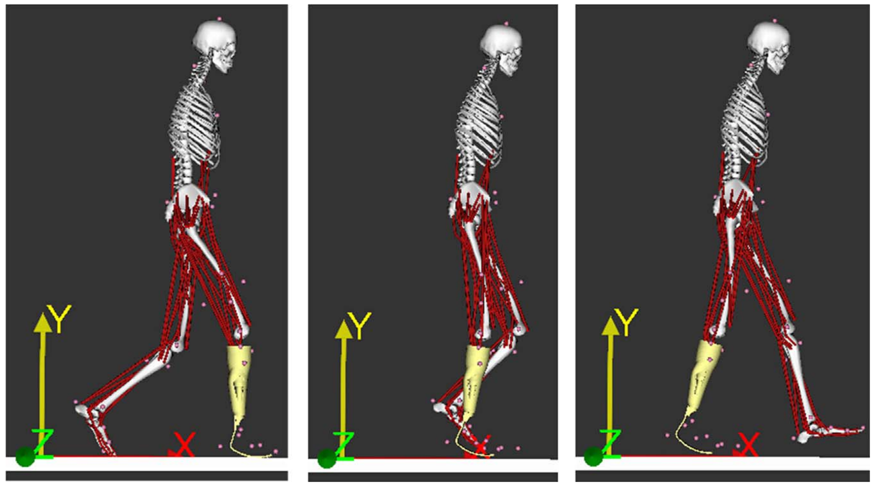

Fig. 6. Human motion simulation in OpenSim.

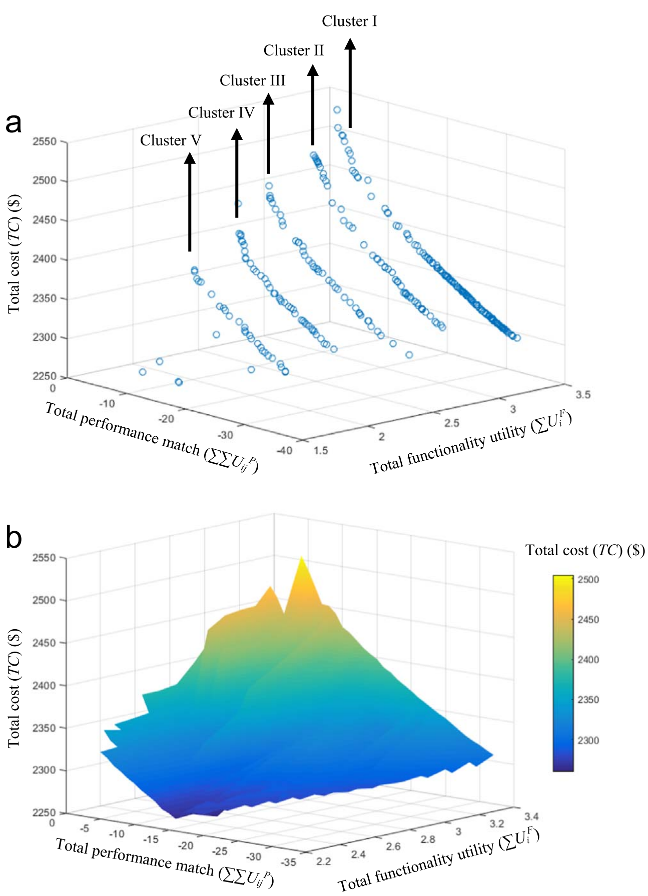

Fig. 7. Results from solving the MDO problem: (a) five clusters of Pareto-optimal solutions and (b) the interpolated 3-D surface.

prosthesis components can then be predicted by ANN-based metamodels.

The NSGA-II was applied to solve the MDO problem for additive manufactured customized TT prostheses. The chromosome population size was 600, the Pareto fraction was 0.5, and the maximum number of optimization iteration was set to be 800. The 3-D plot of the Pareto-optimal solutions is shown in Fig. 7(a), where each point represents a full set of design variables including the components, materials, AM processes and dimensional parameters for all four customers. The three objectives of the MDO, i.e. the total cost (*TC*), functionality utility $\left(\sum U_i^F\right)$, and performance match $\left(\sum\sum U_{ij}^P\right)$, are marked in the three axes of the 3-D Pareto plot. For clearer visualization of the variation trend along one axis with respect to the other two, an interpolated surface is calculated from the points in Fig. 7(a) and displayed in Fig. 7(b).

Trade-offs among the three dimensions can be observed from the interpolated surface. An increase in either the total functionality utility or performance match leads to higher total costs. As discussed in Section 2.2.3, efforts in customizing the design and setting/maintaining different AM processes for the same type of components will result in extra costs due to additional resources and manpower required. As shown in Fig. 7(a), the Pareto-optimal solutions form five distinct clusters. All the scattered points in the *same* cluster represent TT prosthesis designs with the *same* selections of components, materials, and AM processes, while these points differ from each other in terms of their dimensional parameters. Table 6 shows the selected TT prosthesis components, materials, and AM processes in Clusters I–V for all four customers in two market segments. The values of the total functionality utility $\left(\sum U_i^F\right)$ and maximum total cost (TC_{max}) of Clusters I–V are shown in Table 7.

It can be observed from Fig. 7(a) and Table 7 that the Pareto-optimal solutions in Cluster I have the largest total functionality utility compared with the other clusters. Meanwhile, the solutions in Cluster IV have the lowest maximum total cost value. The final decision on which cluster of design solutions to be accepted needs to be made based on the manufacturer's market strategies. For example, if the manufacturer aims to provide the best functionalities and the most customized designs while a high cost is acceptable, the design solutions in Cluster I will be appropriate choices. However, if the manufacturer makes an opposite strategy to reduce costs by taking the risk of compromising the functionalities and performance customization, the design solutions in Cluster V may be preferred. The proposed methodology also enables

Table 6
The selected components, materials, and AM processes different clusters of the Pareto-optimal solutions.

Solution clusters		**Cluster I**				**Cluster II**				**Cluster III**				**Cluster IV**				**Cluster V**			
Market segments (*i*)		**1 (“Casual Users”)**		**2 (“Sporty Users”)**		**1 (“Casual Users”)**		**2 (“Sporty Users”)**		**1 (“Casual Users”)**		**2 (“Sporty Users”)**		**1 (“Casual Users”)**		**2 (“Sporty Users”)**		**1 (“Casual Users”)**		**2 (“Sporty Users”)**	
Customers		C_{11}	C_{12}	C_{21}	C_{22}	C_{11}	C_{12}	C_{21}	C_{22}	C_{11}	C_{12}	C_{21}	C_{22}	C_{11}	C_{12}	C_{21}	C_{22}	C_{11}	C_{12}	C_{21}	C_{22}
Socket	***Mr***	Rubber	Rubber	Rubber	Rubber	Rubber	Rubber	Rubber	Rubber	Rubber	Rubber	PP	PP	Rubber	Rubber	PP	PP	PP	PP	PP	PP
	Pr	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA	SLA
Protective cover	***S***	Y	Y	Y	Y	Y	Y	N	N	N	N	Y	Y	N	N	N	N	N	N	N	N
	Mr	PP	PP	ABS	ABS	ABS	PP	N.A.	N.A.	N.A.	N.A.	ABS	ABS	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
	Pr	SLA	SLA	FDM	FDM	FDM	SLA	N.A.	N.A.	N.A.	N.A.	FDM	SLA	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Foot	***S***	Y	Y	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y	N	N
	Mr	ABS	AlSi10Mg	N.A.	N.A.	ABS	AlSi10Mg	N.A.	N.A.	ABS	AlSi10Mg	N.A.	N.A.	ABS	AlSi10Mg	N.A.	N.A.	ABS	AlSi10Mg	N.A.	N.A.
	Pr	SLA	SLM	N.A.	N.A.	SLA	SLM	N.A.	N.A.	FDM	SLM	N.A.	N.A.	FDM	SLM	N.A.	N.A.	FDM	SLM	N.A.	N.A.
Blade	***S***	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
	Mr	N.A.	N.A.	AlSi10Mg	Ti64	N.A.	N.A.	AlSi10Mg	Ti64	N.A.	N.A.	AlSi10Mg	Ti64	N.A.	N.A.	AlSi10Mg	Ti64	N.A.	N.A.	AlSi10Mg	Ti64
	Pr	N.A.	N.A.	SLM	SLM	N.A.	N.A.	SLM	SLM	N.A.	N.A.	SLM	SLM	N.A.	N.A.	SLM	SLM	N.A.	N.A.	SLM	SLM

Table 7
The total functionality utility and maximum total cost values in Clusters I–V.

	Cluster I	Cluster II	Cluster III	Cluster IV	Cluster V
Total functionality utility ($\sum U_i^F$)	3.40	3.30	2.90	2.80	2.40
Max. total cost (TC_{max}) ($)	2530.68	2473.52	2451.06	2426.54	2358.77

customers' direct participations in the design of additive manufactured customized products. Some decision variables, such as the selection of optional components and/or materials, can be pre-determined by customers themselves based on their specific requirements, while the other decision variables (e.g. detailed parametric designs or selections of AM processes) that are not explicitly meaningful to customers can be determined by the designer during the MDO process. As demonstrated by the case study, the MDO result provides a collection of feasible solutions that help designers or manufacturers identify the optimal components, materials, AM processes, dimensional parameters, and the predicted values of cost and customer utility.

Other than the TT prosthesis example illustrated in this case study, the proposed MDO method can also be applied in other additive manufactured customized products. Sports goods, such as a bicycle, can be an example [30]. Design of the frame and seat can be optimized to fit the cycler's weight, height, and their preferred racing types (e.g. road racing, mountain bike racing, and acrobatics etc.). Helmets, sneakers, and skateboards are also among the potential sports products that can benefit from the proposed MDO methodology.

4. Conclusions

In this research, we formulated a multidisciplinary design optimization (MDO) problem for additive manufactured customized products. By searching for the optimal selection of components, materials, additive manufacturing (AM) processes, and dimensional parameters, the MDO aimed to maximize the functionality utility, match personal performance requirements, and minimize the total cost. Three disciplines, i.e. customer preference modeling, AM production costing, and structural mechanics, were incorporated in the MDO problem. Dimensional restrictions, deformation avoidance, and the limited availability of AM processes for each type of material were formulated as constraints in the optimization. A non-dominated sorting genetic algorithm with the proposed chromosome encoding pattern was used to solve the MDO problem. The proposed methodology was illustrated in the case study of designing additive manufactured trans-tibial prostheses for various customers and market segments. Five distinct clusters of Pareto-optimal solutions were obtained from the MDO, showing trade-offs among the functional utility, personal performance matching, and total cost. The MDO provided a set of feasible design solutions from which the manufacturer would select the appropriate ones based on its market strategy. In this research, only simple personal performance requirements, such as components' sizes and weights, were considered. In future work, more complicated requirements can be modeled and incorporated in the MDO. Furthermore, various other optimization objectives or constraints, such as those concerning logistics and procurements, may be added to the MDO formulation in future research.

Conflict of interest

We wish to confirm that there are no conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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