A Decision-Support Tool for the Choice of Fabrication Routes in the Context of Mass Personalization

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Abstract

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In the saturated competitive markets of today, Mass Personalization (MP) is getting more and more attention. MP refers to the affordable fabrication of personalized products where the customer is involved from the beginning of product life-cycle (design phase). In order to keep personalized products *affordable*, it is important to select the most cost-effective fabrication route for each individualized order. To do so, this study proposes a Web-based Personalized Manufacturing Consulting System (WebPMCS) towards selecting the most cost-effective processes/resources for mass personalization in the on-demand manufacturing context. The proposed tool includes a Graphical User Interface (GUI), a cost-estimation model, and a relational database. In this document, we explain the steps towards WebPMCS design and development. Then, we adapt WebPMCS to Spark Assisted Chemical Engraving (SACE). By the aid of this case-study, we validate the tool, and determine the most cost-effective fabrication routes for several personalized orders. Finally, we suggest using multi-head machines for SACE personalized fabrication and prove its benefits using WebPMCS. The proposed tool acts as an advanced calculator and a process/resource selector, and is aimed to be used as an enabling module for *industry 4.0* manufacturing philosophy.

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Last but not least, I should thank my friends for lightening the path with their limitless encouragement and friendship.

Nomenclature

Input	
$\mathrm{mue}_{t,i}$	the design effect on the material usage of task-choice$_{t,i}$ (the i^{th} choice of task t)
$\mathrm{mpe}_{t,i}$	the design effect on the material price per unit of task-choice$_{t,i}$
$\mathrm{ee}_{t,i}$	the design effect on the equipment usage time of task-choice$_{t,i}$
$\mathrm{le}_{t,i}$	the design effect on the labor working time of task-choice$_{t,i}$
bs	batch size; the number of final products required with the personalized design
Parameters	
$\mathrm{fv}_{t,i}$	1 if task-choice$_{t,i}$ has variable costs, 0 otherwise (fixed costs)
$\mathrm{a}_{t,i}$	the capacity of task-choice$_{t,i}$; the maximum number of products that task-choice$_{t,i}$ can handle with no extra cost
$\mathrm{et}_{t,i}$	usage time (hr) of the equipment used in task-choice$_{t,i}$
$\mathrm{ec}_{t,i,n,m}$	the machining head usage cost per hour for the equipment with n machining heads and m tool-electrode heads used in task-choice$_{t,i}$; n=*1* and m=*1* unless the value of the n and m indices are specified
$\mathrm{lt}_{t,i}$	working time of the labor involved in task-choice$_{t,i}$
$\mathrm{lp}_{t,i}$	pay rate of the labor involved in task-choice$_{t,i}$
$\mathrm{mu}_{t,i}$	material usage (measured by the material unit) of task-choice$_{t,i}$
$\mathrm{mp}_{t,i}$	purchasing fee of one unit of the material used in task-choice$_{t,i}$
Output	
$\mathrm{C}_{t,i}$	the cost of task-choice$_{t,i}$ for the personalized order
$\mathrm{Eqp}_{t,i}$	equipment cost of task-choice$_{t,i}$ for the personalized order
$\mathrm{Lbr}_{t,i}$	labor cost of task-choice$_{t,i}$ for the personalized order
$\mathrm{Mat}_{t,i}$	material cost of task-choice$_{t,i}$ for the personalized order
$\mathrm{s}_{t,i}$	1 if task-choice$_{t,i}$ is selected to be part of the most cost-effective fabrication route for the personalized order; 0 otherwise

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Chapter 1

Introduction

The main goal of this thesis is to design and develop a web-based decision-support tool for specifying the most cost-effective fabrication route in the context of mass personalization. The proposed tool assists in personalized fabrication by selecting the most cost-effective processes/resources for each customer-specific order. It can also evaluate personalization strategies with its advanced cost calculation features. In particular, in this thesis we:

- model the cost of personalized manufacturing considering labor, material, and equipment resources;
- design and develop a web-based tool to accept several user inputs for each personalized order and provide the most cost-effective fabrication route accordingly;
- investigate the Spark Assisted Chemical Engraving (SACE) process as our case-study and provide the most cost-effective fabrication route for several personalized orders using the proposed tool; and
- evaluate SACE multi-head fabrication using the proposed tool and provide corresponding results.

1.1 Motivations

Today's markets tend to become increasingly saturated and competitive. The power of customers has increased in the market and they expect to receive what they want when they want it. Customers are not willing anymore to spend increasing prices for higher qualities but rather would like to get involved in the fabrication process of their desired and potentially complex products with short life cycles (Brettel, Friederichsen, Keller, & Rosenberg, 2014). These are among the factors that have led to the emerge of Mass Customization (MC) and later Mass Personalization (MP). While MC is more about providing a range of purchase options to customers, MP pushes MC a level further by providing customer-specific products through individual customer-company interactions. Implementing personalization could bring many benefits to the business such as attracting new customers and keeping current ones highly satisfied by meeting their needs individually with positive customer experience.

In MP, personalized products must be fabricated in such a way to keep the final product affordable and close to mass production prices. Nevertheless, the implementation is not without challenges. For a production system, individualized orders come with unique features which could require extra work such as different machine setups. In addition, individualized products tend to become more complex and fabricating them could be challenging. Further, as multiple fabrication routes with different costs could be possible in a production system, it is important to select cost-effective processes and resources for individualized orders. At the end, the production system might need to work in an on-demand environment, where customers place their unique orders and the system fabricate per demand. These factors must be taken into account to ensure that the final product remains affordable and does not hamper MP implementation. Advanced manufacturing technologies (such as SACE, 3D printing, Wet Etching, and Laser Machining) could be a solution to some of these concerns. Being able to fabricate complex products from a single Computer-Aided Design (CAD) file and generally lower setup and tooling costs for different designs have made advanced fabrication technologies attractive for personalization applications. They also provide flexibility and easy configuration as customer-specific designs change; therefore, they could be effectively used on demand (Hu, 2013). There is still the challenge of finding the appropriate process/resources for each customer-specific order to ensure affordability of final products.

The main motivation of this study is to enable personalized manufacturing by providing the most cost-effective fabrication route for individualized orders so as to reduce the personalized production cost. Personalized process/resource selection could be challenging as multiple resources might be involved in the production cost (namely labor, equipment, and material) and several parameters and considerations might change as different individualized orders (with unique features) enter the system. For instance, a *complex design* or a *high batch size* can affect the *equipment* usage of a fabrication task. For similar reasons, this decision-making could become lengthy if done manually by the fabricator. The decision-making should be done automatically in order to ensure that personalized orders are fabricated in a timely manner. At this time, to the best of our knowledge, there is no thorough model or approach to select cost-effective fabrication routes based on personalized orders.

Considering the need for automatic personalized process/resource selection, and as a first attempt, this study proposes a scalable web-based decision support tool. As our main contribution, the proposed tool considers process/resource possibilities in form of *fabrication routes* and models the *production cost* as well as the effect of *personalized designs* and *batch sizes* on the decision-making process. The most cost-effective fabrication route is selected by the tool automatically for each individualized order.

1.2 Summary of Contributions

The core contribution of this thesis is to enable mass personalization in on-demand manufacturing by selecting the most cost-effective fabrication route for each personalized order. To do so, we first estimate the cost of personalized fabrication considering labor, material, and equipment resources. In the cost estimation procedure, we take into account the effect of the *personalized design* and the *batch size* on the production tasks. Second, we design and develop a web-based tool consisting of a user interface, database, and server-side code for process/resource selection. We include the cost estimation model in the web-based tool. Third, we specify the most cost-effective fabrication route for nine SACE personalized orders. Finally, we show that multi-head machining could reduce the cost of the SACE personalized fabrication and make the final product more affordable.

1.3 Outline

Chapter 2 discusses MC, MP, and manufacturing process/resource selection along with the related literature. Chapter 3 explains the methodology exploited in this thesis. All the aspects related to the implementation of the proposed tool and its adaption to SACE technology is discussed in chapter 4. Chapter 5 provides the experimental result related to validating the proposed tool, personalized process/resource selection, and evaluating the multi-head machining strategy for the manufacturing system. Finally, chapter 6 concludes the thesis and provides future research topics related to this study.

Chapter 2

Literature Review

This chapter provides a review of the literature related to process and resource selection for personalized manufacturing. Since Mass Customization (MC) and Mass Personalization (MP) are related concepts and have similarities, this chapter starts by discussing prior studies on Mass Customization and its levels (sections 2.1 and 2.2). Then, related state of the art on Mass Personalization (section 2.3) is provided while comparing MC and MP concepts using scholar points and investigation results. Next, section 2.4 elaborates on technologies and methodologies used in the literature for enabling mass personalization. Section 2.5 discusses different approaches in process and material selection in manufacturing. Finally, section 2.6 concludes the chapter by summarizing the main points and highlighting the current gaps of the literature.

2.1 Mass Customization

In the global competition toward cost-effective products, manufacturing companies have realized that customers are not willing to pay incremental high prices for quality improvements anymore. On the other hand, market saturation has been growing, increasing the buyer power in markets where the customer can easily order and purchase variety of products from different companies and suppliers. There has also been a growing demand for customized products with short life cycles where the customer enjoys being involved in making the final product. All of the mentioned factors among others have led companies into focusing on customization, low time-to-market and incorporating differentiation and individualization in their products and services (Brettel et al., 2014). Customization not only becomes helpful for meeting customers' need, stimulating customer consumption, and attracting potential customers but also promotes the business development of the company (Helander & Jiao, 2002). Choi, Lee, and Taylor (2016) found out that customers prefer personalized products over standardized ones for personal use or even as a gift when there is a reversibility choice. This trend of favoring variety and moving from mass production to customization and still remaining inexpensive for customers let the concept of Mass Customization (MC) emerge in the late 1980s (Da Silveira, Borenstein, & Fogliatto, 2001).

Mass customization pays more attention to customers and involves them in the final product. Based on Business Dictionary (2018), Mass Customization is "Production of personalized or custom-tailored goods or services to meet consumers' diverse and changing needs at near mass production prices". Ghiassi and Spera (2003) defined MC as a production infrastructure which includes many partners (such as suppliers, customers and other companies) and can be quickly adopted to produce customized products. Despite the existence of different MC definitions, there might be a doubt in possibility of Mass Customization whatsoever. Customization and mass production has been traditionally opposed to each other and having them together might seem unrealistic. Selladurai (2004) investigated the concept of Mass Customization, this seeming paradox, and discussed why MC is a reality not an oxymoron. They mentioned that Mass Customization has been implemented and used in practice by major firms such as Dell, General Motors, Ford and Toyota in their production and operations facilities. In their literature review, Fogliatto, Da Silveira, and Borenstein (2012) also indicated that MC has been successfully implemented in different sectors such as manufacturing, food industry, electronics, large engineered products, home buildings and mobile phones. They emphasized that MC is a reality today and has application in different sectors. In this research, we confine our attention to manufacturing industry.

2.2 Different Levels of Mass Customization

There has been a debate in the literature regarding the level of customization and the definition of a true Mass Customization. Purists may attribute MC to meeting all customer requirements while Pragmatists see MC as simply providing delivery options for customers (Da Silveira et al., 2001). Hart (1995) stated that the goal of Mass Customization is specifying the range a product or service can be meaningfully customized and, then, providing customization options within that range. They stated that Mass Customization is a customized strategy itself and the way it is implemented depends on the company's needs and capabilities, customers, new technologies available, and the market competency. As a framework for MC implementation, Lampel and Mintzberg (1996) proposed a continuum of strategies. They stated that MC can occur across the value chain as: a) *Segmented Standardization:* customized distribution; b) *Customized Standardization:* customized assembly and distribution; c) *Tailored Customization:* customized fabrication, assembly and distribution; and finally d) *Pure Customization:* customized design, fabrication, assembly and distribution.

Pine (1993) investigated Mass Customizing products and services and proposed five methods as progressive stages: a) Customized Services (tailoring standardized products in marketing and delivery departments before they reach customers); b) Embedded Customizability (offering products and services which can easily adapt to individual needs during use); c) Point-of-Delivery Customization (performing customized production steps at the point of sale); d) Providing Quick Response (reducing time throughout the company's value chain, accelerating product development, and offering short-time delivery of products); and e) Modular Production (creating standard modular components which can be configured to produce a variety of customized products).

Based mostly on empirical observations, Gilmore et al. (1997) addressed customization levels by proposing four approaches of Mass Customization. They stated that the best option usually lies in a mix of some or all of these approaches. The customization levels proposed were: a) *Collaborative:* there is a dialogue between individual customers and customizers in order for customers to communicate their needs and receive customized products; b) *Adaptive:* designing and offering one standard, but customizable, product which makes it possible for customers to alter its functionality on their own in different usages; c) *Cosmetic:* a standard product is packaged differently for each customer; and d) *Transparent:* the company adapts products to individual needs where the customers' specific needs are predicted and deduced by the company and the customer is not told that he or she is receiving a "customized" product or service.

Later, Da Silveira et al. (2001) derived an eight-level Mass Customization framework by combining other related studies in the literature. In their framework, the top level (level 8) is *design* (collaborative projects according to customer individual needs). Level 7 is *fabrication* (utilizing predefined designs so as to provide customized products). Level 6 refers to *assembly* (arranging modular components to customer's requirements). Level 5,4, and 3 provide *additional services*, *additional custom work* and *customized packaging/distribution*, respectively. Level 2 is about *usage* and products that can be adapted and customized by the customer after delivery. Finally, level 1 refers simply to providing *standardized products*.

Publishing a two-dimensional framework for MC, Duray, Ward, Milligan, and Berry (2000) and Duray (2002) proposed that MC can be classified based on the customer involvement point in the production cycle and the type of product modularity used. They considered *Design*, *Fabrication*, *Assembly* and *Use (Delivery)* as four points of customer involvement in the production cycle. Referring to the research conducted by Ulrich and Tung (1991) in modularity types, they also considered six modularity types: component-sharing modularity, component-swapping modularity, cut-to-fit modularity, mix modularity, bus modularity and sectional modularity. In these modularity types, component-sharing and cut-to-fit were considered closer to providing original unique designs while the rest provided standardized and repeatable components. Considering customer and modularity, they proposed four groups based on the level of Mass Customization as follows. *Fabricators* involve both customers and modularity types in design and fabrication; this group uses component-sharing and cut-to-fit modularity types to produce customized products. *Assemblers* involve both customers and modularity in assembly and delivery. They do assemble-to-order manufacturing by providing customers with a predetermined set of choices. In the *Modularizers* group, modularity is incorporated in design and fabrication while customers are involved in assembly and delivery. In other words, non-customizable modularity happens in design and fabrication whereas customizable modularity is done at assembly and delivery, where the customer requirements are specified. *Involvers* include customers in design and fabrication stages but incorporate modularity in assembly and delivery (use). In this group, standard models are combined to meet customer requirements. The customer is involved initially by communicating required specifications but no new module or product is fabricated based on the received information. This initial customer involvement just seems to provide a feeling of customization and ownership for the customer, without having any effect on production planning or process control.

Wikner and Rudberg (2001) indicated that demand includes four aspects: a) what, b) How much, c) When and d) Where. Each of these aspects act like certain or uncertain inputs to the decision making process. The authors stated that these four inputs should be specified from a supply perspective before the customer order is completely known. They defined the term Customer Order Decoupling Point (CODP) as a separator between decisions made under certainty and decisions made under uncertainty. They also investigated four of the most frequently CODPs: Engineer-to-Order (ETO), Make-to-Order (MTO), Assemble-to-Order (ATO) and Make-to-Stock (MTS). A typical sequential approach to CODP is illustrated in 2.1.

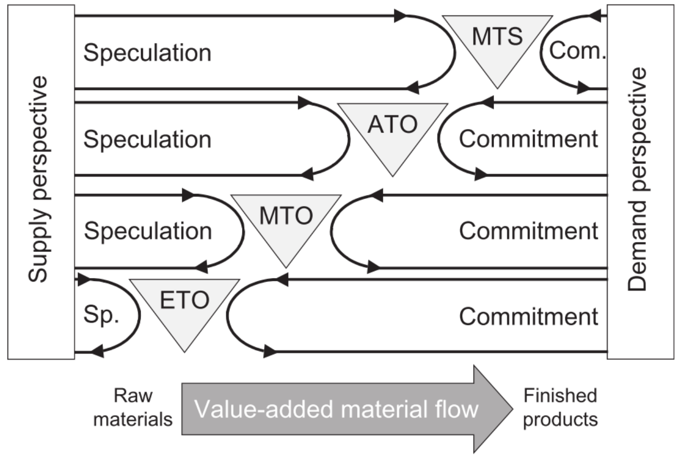

Figure 2.1: CODP - the further downstream CODP is positioned the more activities are done under uncertainty (speculation) (e.g. ETO has the most order commitment) [adopted from (Wikner & Rudberg, 2001)]

Later, Rudberg and Wikner (2004) extended the work of Wikner and Rudberg (2001) by proposing a two-dimensional framework for decision-making in Mass Customization. They differentiated engineering and production activities and considered them as two dimensions, stating that the *production dimension* takes care of material flow while the *engineering dimension* happens when a new product is designed. They showed that customer involvement with different levels of intensities at either of these two dimensions can result in various MC levels.

Tien (2006) also proposed a framework for Mass Customization by considering the customer order penetration point (COPP) which separates the supply and demand parts of the value chain. They stated that the degree of Mass Customization increases as the COPP moves upstream the value chain (from customer to supplier); COPP occurring at the customer level gives mass production, COOP at the retailer level gives Make-to-Stock with minor possible customization, COOP at the assembler level is in fact the Assemble-to-Order level with partial customization, COOP at the manufacturing level is referred to as Make-to-Order, and finally COOP at the supplier level provides the highest degree of MC in this framework and is named as real-time Mass Customization. The term real-time Mass Customization in their framework was first introduced by Tien, Krishnamurthy, and Yasar (2004) representing the simultaneous and real-time management of supply and demand chains.

2.3 Mass Personalization

The terms Customization, Mass Customization (MC), Personalization and Mass Personalization (MP) have been defined differently in the literature and have sometimes been used interchangeably (Sunikka & Bragge, 2009). Although the difference between Customization and Mass Customization and, also, between Personalization and Mass Personalization has been often neglected or perceived as obvious (e.g. *Mass* Customization: the customization of high volumes of products), some researchers do distinguish Mass Customization from Personalization. Several studies have treated MC and Personalization as different concepts (Gilmore et al., 1997; Hu, 2013; Kumar, 2007; Montgomery & Smith, 2009; Wang et al., 2017; Yao & Lin, 2016) while some have used them interchangeably (Peppers, Rogers, & Sengupta, 1995; Ricotta, Costabile, et al., 2007). Among researchers who consider a difference, there is a consensus that the term Personalization is associated with a) a company-driven process; b) marketing concepts, especially personalized communications; and b) internet context (Sunikka & Bragge, 2009).

Kumar (2007) proposed a strategic transformation from Mass Customization (MC) to Mass Personalization (MP). They proposed that MP pushes MC a level further by transforming the market-of-few of MC to the market-of-one of MP. In other words, they declared that MC provides variety in market niches while MP has a market segment of one.

Tseng, Jiao, and Wang (2010) investigated the design for MP. They stated that as opposed to customization which focuses on meeting explicit customer needs in market segments, personalization aims at eliciting inherent customer needs in one-to-one interactions and meeting them in a market-of-one. They mentioned that customers are not considered in MC as individuals in the product life-cycle (from product conception to delivery, usage, service or disposal) since the conventional surveys or interviews done in MC fail to extract customer latent needs. They argued that some customers are reluctant to reveal their inherent needs and some do not know themselves either. They, then, indicated that mass personalization emphasizes effective and efficient customer satisfaction by offering personalized unique products with positive customer experience.

Hu (2013) differentiated mass production, Mass Customization and personalization from each other. They stated that mass production has a focus on economy of scale while Mass Customization paradigm is an economy of scope and personalization values differentiation (see figure 2.2). Mourtzis and Doukas (2014) also considered a difference and investigated the evolution of manufacturing paradigms as shown in figure 2.3.

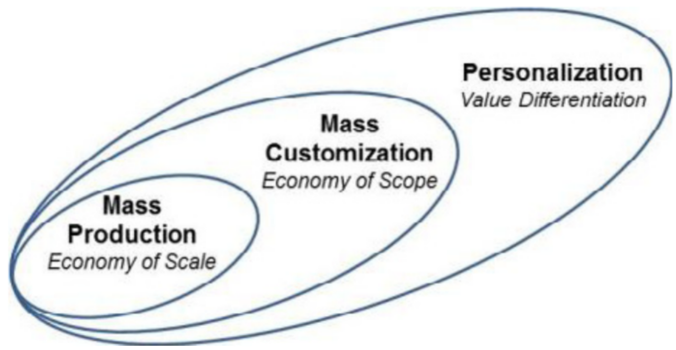

Figure 2.2: Goals of manufacturing paradigms [adopted from (Hu, 2013)]

Tiihonen and Felfernig (2017) made a distinction between MC and MP. They stated that Mass Customization provides customized products and services with nearly mass production costs, but a major side-effect of MC is the customer confusion it creates with the many options it provides for customers. They proposed that personalized products can mitigate this challenge by personalized communication with the customer and meeting their need individually.

Wang et al. (2017) mentioned that there are some limitations to Mass Customization which bring the necessity of personalization. Based on their investigation, in Mass Customization: there is no strong customer participation in the design phase and potential product varieties and combinations are all pre-specified by designers (no direct customer involvement). They proposed a framework for personalized production, based on the industry 4.0 concept, to overcome the gap between Mass Customization and mass personalization.

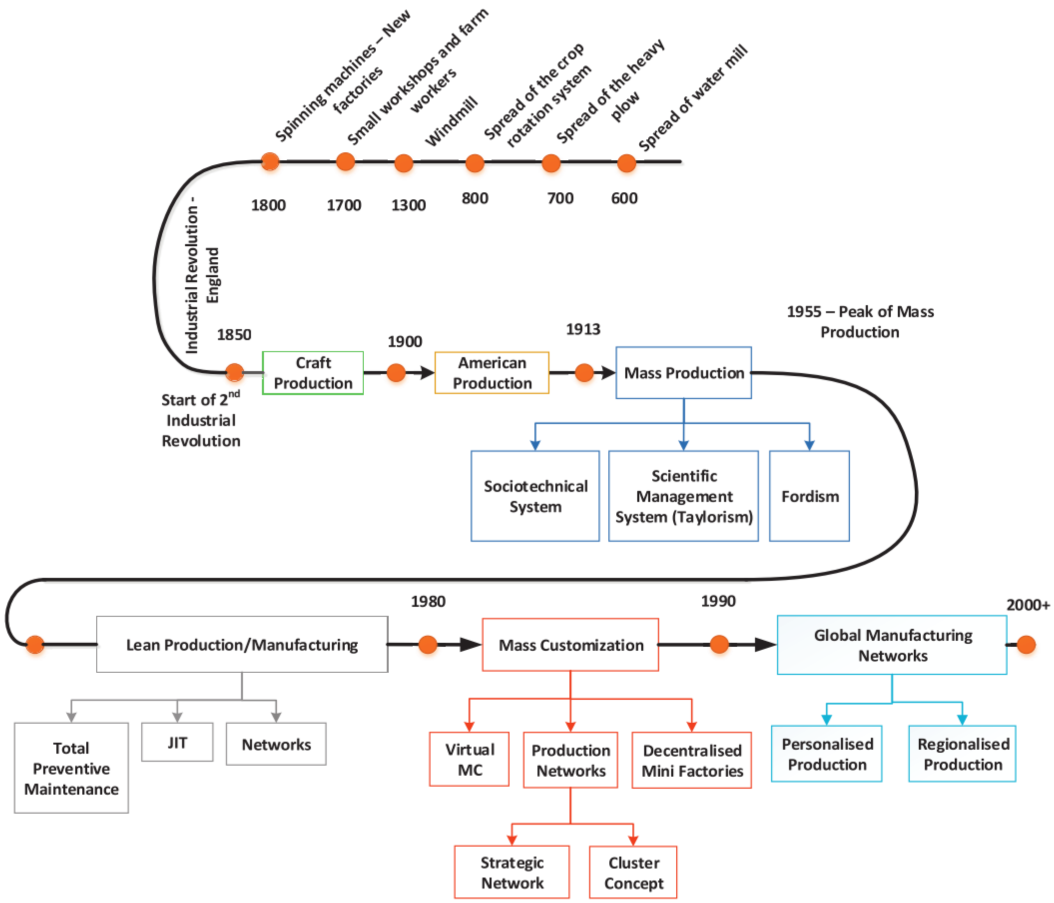

Figure 2.3: The Evolution of Manufacturing Paradigms [adopted from (Mourtzis & Doukas, 2014)]

Table 2.1: Comparing mass production, MC, and Personalization (MP) in terms of goal, focus, customer role, product characteristics, product structure, production system, and key features (Blecker & Friedrich, 2006; Hu, 2013; Mourtzis & Doukas, 2014)

	Mass Production	Mass Customization	Personalization
Goal	*Economy of Scale* low-price production affordable for all	*Economy of Scope* involving customers in production and providing affordable customized products	*Value Differentiation* involving customers in design and providing affordable individualized products
Focus	stability and control over the process	customization and variety in a flexible integrated system	individualization in on-demand manufacturing systems
Customer Role	**buy**	**choose** buy	**design** choose buy
Desired Product Characteristics	Quality **Cost**	Quality Cost **Variety**	Quality Cost Variety **Efficacy**
Product Structure	common parts	common and custom parts	common, custom and personalized parts
Production System	Dedicated Manufacturing Systems (DMS)	Reconfigurable Manufacturing Systems (RMS)	On-Demand Manufacturing Systems (OMS)
Key Features	Stable demand Homogeneous market Low cost and standardized products and services Long product life-cycles	Fragmented demand Different market niches Low-cost and customized products and services Short product life cycle	Individual demand Market-of-one Low-cost and personalized products and services Short product life-cycle

2.4 Mass Personalization Enablers

Mass Personalization enablers are considered as the technologies and methodologies which support MP implementation. Proposing a paradigm from mass production to customization and personalization, Hu (2013) stated that mass production was enabled by interchangeability (randomly selecting and assembling parts together), moving assembly lines (bringing machines to workers), Division of Labor (workers focusing on specialized tasks) and Scientific Management (improving labor productivity by time studies, work training etc.). They proposed that MC was enabled later by Product Family Architecture (providing variety in the final product by modularization), Reconfigurable Manufacturing Systems (systems able to adjust their production capacity and functionality with respect to sudden market changes) and Delaying Differentiation (delaying the point where the product is customized) to provide varieties of products to customers. This study indicated that the active presence of the internet, advanced computing systems, and responsive manufacturing technologies are among the key enablers for providing personalized products for individual needs and preferences. They proposed that personalization is enabled by having open product architecture, personalization design, on-demand manufacturing system and cyber-physical systems in order to let customers involve in design, manufacturing and supply while having customers' need met rapidly. As declared in their research, the *open product platform* in personalization let products have different kinds of modules: common modules (shared across the platform), customized modules (customers choose from choices), mix and match, and personalized modules (customers design their own module); all of the modules have appropriate electrical, mechanical and informational interfaces to assemble and disassemble easily. The *Personalization design* enabler involves customers in design at different levels, from novice to experienced, and aims at providing an environment in which customers can make changes and perform creative design and, thereafter, visualize the ramification of their choices and the integration of personalized modules. Furthermore, *on-demand manufacturing system* ensures rapid response to customer demands by providing manufacturing flexibility and easy configuration as the personalized design changes. For example, Additive manufacturing which creates objects from a CAD model cost-effectively (Savitz, 2012) is one of the personalization enabling technologies. Finally, they stated that *Cyber-Physical Systems* (CPS) integrate physical design and manufacturing components with computational tools in order to support the collaborative distributed design approach and on-demand manufacturing which exist in personalization. They mentioned a number of cyber-physical systems needed for personalization: a) user-interface tools (to support users as they design and/or collaborate with other designers); b) algorithms to identify potential new markets and products; c) advanced analysis tools to verify the reliability, manufacturability and safety of personalized designs; and d) tools to support flexible assembly systems and supply chain management for providing a variety of production mix.

Wang et al. (2017) stated that as new industrial revolutions have been approaching (from Industry 1.0 to Industry 4.0), production paradigms have had a change from craft production to mass production, Mass Customization and Finally Mass Personalization (as shown in figure 2.4). The fourth industrial revolution or Industry 4.0 is a term for value chain organization based on different technological concepts namely radio frequency identification, cyber-physical systems (CPS), the Internet of Things (IoT), Internet of Services (IoS), cloud computing and data-mining (Gilchrist, 2016; Wang et al., 2017).

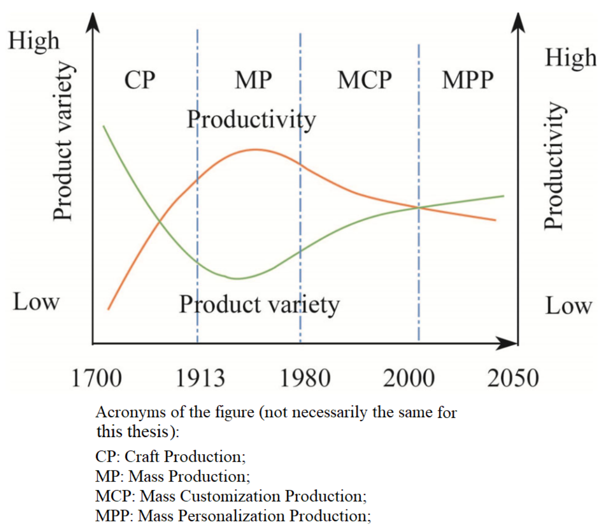

Figure 2.4: evolution of production paradigms (Wang et al., 2017)

Wang et al. (2017) argued that industry 4.0 supports the manufacturing strategy of mass personalization. They stated that industry 4.0 makes MP possible and has four components: a) CPS; b) mobile, cloud computing and the Internet of Things (IoT); c) big data, data mining and knowledge discovery; and d) Internet of Services (IoS). They proposed that category (a) connects the virtual and real world by making physical systems network compatible and capable of storing and analyzing data. Category (b) makes objects capable of sharing information and collaborating with each other while automatically communicating with the internet; this way, operators will be notified of any problem in different manufacturing steps. Category (c) helps in extracting knowledge from the large amounts of data obtained from different sources in order to make the correct decision at the right time. Finally, category (d) makes it possible for vendors to offer their services via internet and let multiple suppliers add value into their services. Their research proposed a mass personalization framework (see figure 2.5) comprising network layer, IoS, warehouse management system, manufacturing execution system, CPS, and enterprise information system.

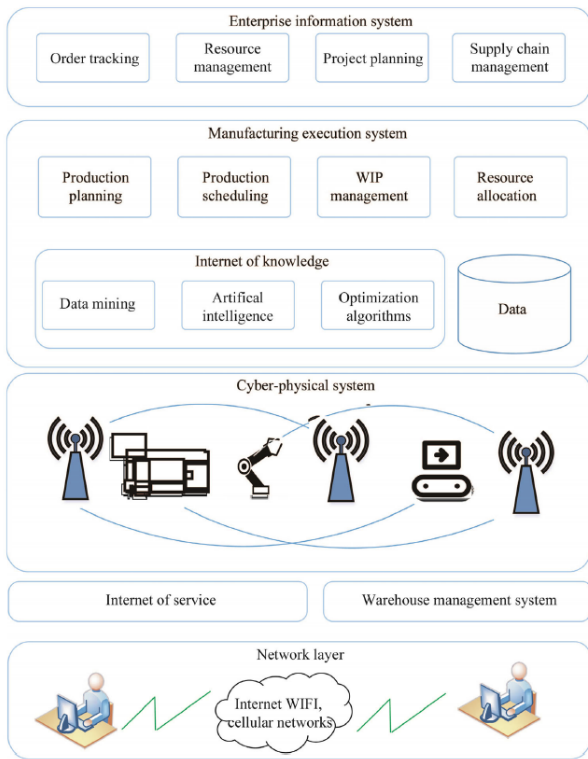

Figure 2.5: mass personalization framework [adopted from (Wang et al., 2017)]

2.5 Process and Material Selection in Manufacturing

The great effect of design on the final product cost (Whitney, 1988) and also the need for post-processing and rework increase the interest to seek concurrent engineering (Giachetti, 1998). Giachetti (1998) defined *Concurrent Engineering (CE)* as *"the parallelization of the* *activities involved in the product development process".* They mentioned that "Design for Manufacturing (DFM)" is an important aspect of CE which considers manufacturing from early stages in product development to reduce product development time, quality issues and final cost. Their study indicated that Material and Processes Selection (MPS) is a potentially important decision-making activity in DFM which is difficult due to the existence of multiple criteria of unequal importance and flexible soft requirements. They stated that Multi-Criteria Decision Making (MCDM) methods are best to solve MPS problems.

Regarding the MPS problem, there has been several studies in the literature. Giachetti (1998) provided a prototype material and manufacturing process selection system considering three modules for decision-making (see figure 2.6). In their system, *mechanical* and *physical* features of *Materials* and *geometric*, *technological*, and *production* characteristics of *Manufacturing Processes* are taken into account as decision-making criteria. Some examples of these criteria are indicated in tables 2.2 and 2.3. In material and process selection modules (as indicated at figure 2.6), they ranked feasible materials and processes based on product requirements using possibility theory (Dubois & Prade, 2012), calculating a compatibility rating vector for each material and manufacturing process. Then, these rating *vectors* are aggregated to result in rating *numbers* for each material and process. In order to consider preference of different *combinations* of materials and processes, material and process ratings are joined based on the feasibility of material/process combinations. A partially ordered set of feasible material/process combinations is given to the *Aggregation Module* to let it rank materials and processes using multi-criteria decision making. In short, their decision-support system receives product requirements, their precision level, in addition to an importance weight as the input and provides process/material decision based on the compatibility of material/process capabilities and product profile requirements.

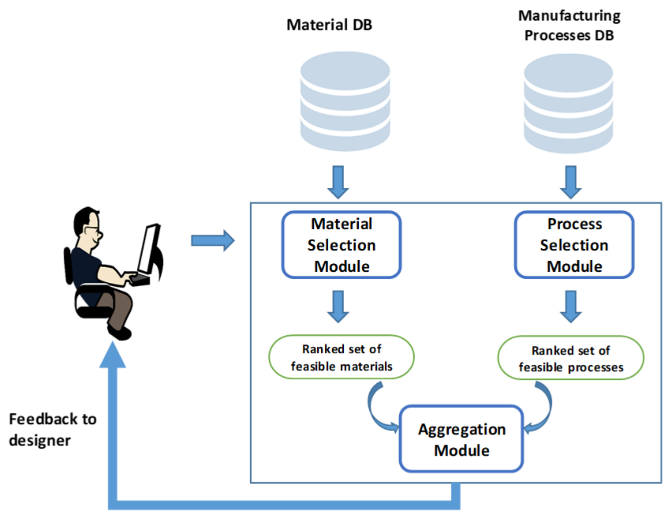

Figure 2.6: Material and process selection architecture (Giachetti, 1998)

Table 2.2: Examples of material selection (Giachetti, 1998)

Material Selection Criteria	
Mechanical	hardness, stiffness/density, yield strength, ...
Physical	cost/kg, thermal conductivity, corrosion resistance, ...

Table 2.3: Examples of manufacturing process selection criteria (Giachetti, 1998)

Manufacturing Process Selection Criteria	
Geometric	undercuts, overall dimension, shape and complexity, ...
Technological	tolerance, surface finish, ...
Production	processing cost/part, production volume, time-to-market

Zha (2005) differentiated process/material “requirement” from “option” and proposed a framework to select manufacturing processes and materials in a way to meet all critical design requirements with the minimum cost. They defined “requirement” as something needed by the emerging design concerning either material (yield strength, hardness etc.) or process (e.g. production rate, lead-time, overall production quantity); while “options” denoted possible processes and materials that the designer tries to select.

In this context, Chen, Gupta, and Feng (2000) and Zha (2005) categorized design requirements as follows:

(1) *Material Requirement:* they are stated in needed ranges of yield strength, hardness, operating temperature, etc.

(2) *Process Requirement*

- *Form Requirement:* these are stated as product size, form feature types (number of holes, undercuts, tapers etc.), surface finish, tolerances, etc.
- *Production Requirement:* these requirements include required ranges of production rate, production quantity, lead-time, etc.

Considering these definitions, Zha (2005) proposed a fuzzy knowledge-based method for Multi-Criteria Decision Making (MCDM) to find a process sequence that meets design requirements with the minimum total production cost. They took into account the cost of material, process (labor and capital cost), tooling, and setup. Their system had three major steps: 1) Eliminate Unacceptable Alternatives, 2) Evaluate Candidates and Customization, and 3) Make Decision. The decision-making was done using weighted average rating and fuzzy sets. They provided all this in a Java applet Graphical User Interface (GUI) to act as a Web-based manufacturing consulting service (WebMCSS). Their system, however, did not consider personalization in calculating process/material cost.

Kumar and Singh (2007) presented a system for material selection of progressive die components. This system was used to select materials and determine proper hardness ranges for them. They acquired the needed technical knowledge from technical resources and experienced die designers. Then, they tabulated the information in a set of "if-then" rules. The system accepted user input and provided selected materials as output. Their decision tool was coded in AutoLISP language and was usable via AutoCAD; providing an affordable material selection program for designers.

Almannai, Greenough, and Kay (2008) developed a tool to select appropriate manufacturing automation technologies based on Quality Function Deployment (QFD) technique. As investigated by Cohen (1995), QFD can be described as a systematic approach involving different quality tables which are based on customer needs and product features; QFD outputs the intersection of customer needs and technical requirement, ensuring that product and customer's voice are fully considered in decision-making. After selecting technologies using QFD, Almannai et al. (2008) used Failure Mode and Effects Analysis (FMEA) to identify the associated risk with the selected option in order to highlight trade-offs and concerns for implementation. In other words, QFD determined "the why behind automating and the best alternative technology" while FMEA provided a hint about "what points needs careful attention" when implementing the alternative(s). Their tool helped in decision-making in three stages: a) linking automation investment objectives (coming from management) with evaluation criteria; b) using evaluation criteria to select the best alternative; and c) identifying the potential risk associated with the selected alternative. In the last stage, Normalized Risk Priority Number (RPN) was provided for each failure mode to show the severity and likelihood of the associated potential problems. A high RPN number shows high possibility for the risk element to happen.

Later, Maleque, Sarker, et al. (2010) investigated selecting the optimum material for bicycle frames using two methods: cost per unit property and digital logic. They also used Ashby's material selection chart for initial material screening. The cost per unit property was used considering only one property, strength, as the most critical one. This approach calculated the cost of unit strength for different materials using a mathematical equation and selected the cheapest (lower cost per unit property) material. This study also used Digital Logic method in order to consider multiple properties. First, property requirements were determined using the Ashby's chart and the weighting factors were identified for each property. Second, they scaled the properties and calculated Performance Indexes. Finally, Figure of Merit (FOM) was calculated by taking different costs into account and the optimum material was selected. Both methods led to the same first and second best materials in this experiment.

Berman, Maltugueva, and Yurin (2015) combined Case-Based Reasoning (CBR) and MCDM, proposing a hybrid approach to select construction materials in the field of petrochemistry. They considered different material properties and the closeness of them to predefined conditions and objectives (e.g. required corrosion and heat resistance, operating temperature, and proper cost). Then, they applied CBR to retrieve suitable materials based on previous solutions and used MCDM to either verify and justify the obtained solution suggested by CBR or take decision when CBR fails. More precisely, a "case" as in Case-Based Reasoning included materials formed based on previous models (previous decisions made) and their usage experience. Having this, the case retrieval procedure calculated the distance between new cases using a weighted approach and outputted similar ordered cases from previous experience (considering previous successful solutions). This output was considered as future decision alternatives. Multi-methods MCDM approaches were later used to rank materials from best to worst. In fact, they proposed their approach in form of an Expert System which was able to manage the case library (add, edit, or delete material descriptions), retrieve cases with respect to specified conditions, process the output of case retrieval using MCDM, and explain and preview the results.

Considering that precision and tolerance affect the functionality and manufacturing cost of a product, Sivakumar, Balamurugan, and Ramabalan (2011) presented a methodology using intelligent algorithms for simultaneous selection of best machining processes and part tolerances. The reason behind this simultaneous selection was the effect of the part tolerance on the machining-process selection. For instance, the tolerance could effect equipment accuracy, machining sequence and machining parameters and this all justified considering product tolerance when selecting the best process. They modeled this in such a way to achieve the best manufacturing process with low cost and quality loss. In fact, their objective function aimed at minimizing tolerance stack-up, manufacturing cost, and quality loss. They used genetic algorithm and particle swarm optimization techniques to solve their model.

Later, Uz Zaman, Rivette, Siadat, and Mousavi (2018) emphasized the importance of selecting appropriate materials and manufacturing processes (and their associated machines) for mass personalization and proposed a decision making methodology to select materials and processes for Additive Manufacturing (AM), considering the relationship between product and process data in AM. They used Ashby's material chart for material selection. To continue, they used Analytical Hierarchy Process (AHP) and Simple Additive Weighting (SAW) approaches for ranking the material-process combination. In their research, Design for Additive Manufacturing (DfAM) guidelines were used and the procedure consisted of translation, screening and ranking steps. In the first step (translation), functional specifications such as objective, geometry details and constraints were extracted from the CAD model and a set of requirements related to design, product or process were generated. After that, the methodology screened and ranked materials and manufacturing processes in such a way to come to optimal performance indices. They used material and machine data stored in two databases, a cost model developed by Yim and Rosen (2012), and multi-criteria decision models powered by AHP and Simple Additive Weighting. The model used for calculating overall material cost was a multiplication of *support structure factor* (to capture the cost of additional support structures needed), *recycling factor*, *number of parts*, *part volume*, *material rate per unit weight*, and *material density*.

2.6 Summary of the Literature

In this chapter, we presented a review of studies on mass customization, mass personalization, and process/resource selection. Considering the implementation of process/resource selection in mass personalized fabrication as our goal, this chapter aimed at providing an overview of the relevant concepts as well as identifying the aspects that have received limited attention and require further investigation. We summarize our major findings as follows.

The demand for customized cost-effective products in saturated markets led to the emerge of MC (Brettel et al., 2014; Da Silveira et al., 2001). MP has emerged in order to push MC to a level further (Kumar, 2007; Tiihonen & Felfernig, 2017). Different approaches has been investigated in order to implement MP. For instance, it has been stated that on-demand manufacturing systems along with advanced manufacturing technologies could be used in personalization to fabricate affordable products from complex CAD files (Hu, 2013; Savitz, 2012). It was noted that Material and Process Selection (MPS) is an integral part of Design for Manufacturing (DFM) (Giachetti, 1998) which is important for implementing personalization (Uz Zaman et al., 2018).

In the existing literature, we identified that while process/resource selection and on-demand manufacturing both play an important role in MP, there has been little studies investigating the process/resource selection for MP in the on-demand manufacturing context. In addition, most of the relevant studies have separated the production process from the MPS. In other words, the selection is done based on product requirements and, for instance, a material is selected for a pre-defined fabrication route. This does not consider possibilities of different fabrication routes for varied product requirements. Further, to the best of our knowledge, no study in the literature has considered the effect of batch size and personalized design on the MPS while these factors could lead to different production costs. Moreover, few studies have proposed/developed a decision support tool to automate the MPS process which could be lengthy and inefficient if done manually.

In this study and as a first attempt, we fill the aforementioned gaps to some extent by proposing a web-based decision-support tool in the on-demand manufacturing context for selecting the most cost-effective fabrication route for each personalized order. We consider material, labor, and equipment resources in our decision-making. The tool takes into account the effect of batch size and design on fabrication routes before doing the process/resource selection. In other words, with the user inputs it receives, the tool adapts to individualized customer-specific orders. At the end, we adapt the tool to SACE process, an advanced manufacturing technology which we selected as our case-study. We then validate the tool using the process data, select the most cost-effective fabrication route for nine SACE personalized orders, and show that multi-head machining could reduce SACE production cost.

Chapter 3

Methodology

In this study, we consider a personalized order as a fabrication order with a unique design and a batch size (bs). Several tasks have to be completed in order to fulfill a personalized order, and processing these tasks might require material, labor, and/or equipment resources. Two points are important in fulfilling customer-specific orders. First, each task could be performed in different ways (task-choices) (e.g. using various resources, out-sourcing, in-sourcing, etc.). This creates several possible fabrication routes for each order and some of the routes might be more economically viable than others. Second, features of a personalized order (design and batch size) could affect the manufacturing process. Each design can have unique sets of features which could affect different tasks of a manufacturing process. Batch size can also affect fabrication tasks. In short, there are several possible fabrication routes where their characteristics might change for each personalized order. Considering the mentioned points, we designed a decision support tool for process and resource selection in the context of personalized fabrication. The proposed tool acts as an advanced calculator by estimating the cost of all possible fabrication routes for each personalized order and outputting the most cost-effective fabrication route along with selected task-choices. We denote the tool as "Web-based Personalized Manufacturing Consulting System" (WebPMCS).

Several steps were taken to design WebPMCS. After mapping a given manufacturing process, one to several task-choices were considered for each task within the process map, and the relevant data was collected. Since design and batch size might affect the tasks in terms of equipment processing time, manpower and material usage, we initially considered a standard design (determined by an expert for a given manufacturing technology) and a batch-of-one fabrication (*bs=1*) for designing the tool. In other words, fabricating one (bs=1) standard design is considered the *default personalized order* in our tool. After completing the data collection for a *default personalized order*, we considered several user inputs (related to design and batch size) in the tool so that it can adapt to different customer-specific orders. In other words, if the tool receives a *default personalized order*, no design/batch size effect will be considered, but simpler or more complex designs, or larger batch sizes could have some effect on the aforementioned parameters. For each individualized order, we considered that the user records the effect of the design on the equipment, labor, and material usage. Besides, due to the simpler nature of the batch size effect, we modeled the effect of batch size on all fabrication tasks. Next steps for designing WebPMCS were developing a model for cost-estimation of all tasks using the design and batch size information in addition to a decision-making approach in order to select the most cost-effective fabrication route. The methodology used in this study is explained further in three sections: a) Process Mapping and Task-Choices, b) Cost Estimation of Tasks, and c) Decision-Making Process.

3.1 Process Mapping and Task-Choices

For selecting the most cost-effective fabrication route for every personalized order, we should first map the manufacturing process and define different ways of fulfilling a customer-specific order. This section shows how process mapping is done and how different options for fulfilling tasks are considered.

Process Mapping

A high-level generic manufacturing process map (see Figure 3.1) was taken into consideration. Due to the generic nature of "Order," "Inspection," and "Shipping" tasks (as seen in Figure 3.1), they were excluded from cost-estimation in the tool.

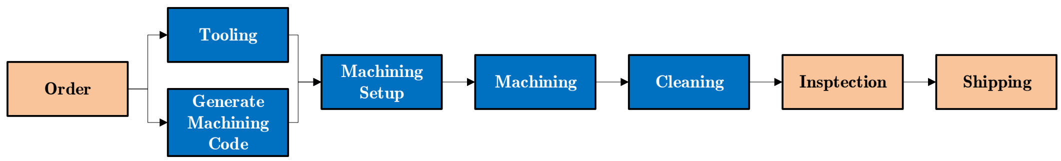

Figure 3.1: High-Level Manufacturing Process Map

For the sake of consistency, tasks in this high-level generic manufacturing process map were further broken down until the last-level tasks are simple enough to require no more than *one type* of a resource at a time (e.g. the task cannot require an *operator* and an *engineer* (two types of labor resource) at the same time). The *high-level generic task (parent)* that was broken down into *last-level tasks (children)* was considered as the "category" of those last-level tasks. For instance, in glass micro-machining using SACE, the high-level task (parent) "Cleaning" can be broken down into the following children: a) rinse the workpiece before fabrication, b) drain electrolyte, c) rinse the glass slide after fabrication, and d) clean the fabricated workpiece. These four tasks (a, b, c and d) are the last-level tasks and their category is "Cleaning." *Last-level tasks* are called "tasks" from this point and are considered as the elements that come together to form a manufacturing route. The following explains how different choices were considered for these tasks.

Task-Choices

Every task in the manufacturing process map can have multiple choices. In-sourcing or out-sourcing a task, using different materials, equipment, or labor as well as purchasing from different suppliers are among the examples of these task-choices. For instance, in glass micro-machining, the electrode used in the *fabricate/order tool electrode* task can be made of stainless steel or tungsten carbide, and the company can either fabricate the tool-electrode in-house or order a pre-fabricated one from a supplier. These options create multiple choices for the task and thereby several routes to fabricate the final product. The proposed model considers task t to have (one to several) task-choice i, where $t \in 1...T$ and $i \in 1...I$. Task-choice$_{t,i}$ corresponds to task-choice i of task t.

The proposed decision-support system (WebPMCS) aims at selecting the most cost-effective task-choices (and therefore the most cost-effective route) depending on the personalized order (see Figure 3.2). Next section provides detailed information on how the cost of each task is estimated for a given personalized order.

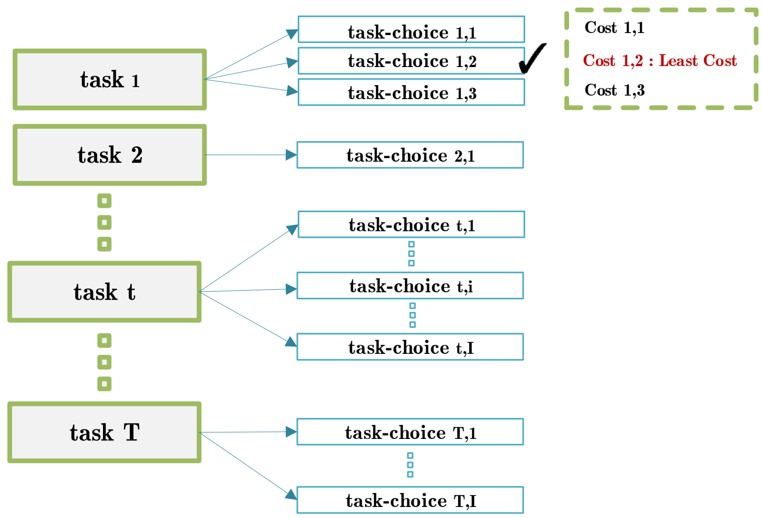

Figure 3.2: one to several task-choices for each task in the process map

3.2 Cost Estimation of Tasks

The cost-estimation approach for the task-choices is inspired by Activity-Based Costing (ABC). *Business Dictionary* (2018) defines ABC as a cost accounting approach which is related to matching the costs with the activities that caused those costs; ABC enables companies to better understand how and where they make profit, where the budget is being spent, and which sections have the greatest potentials to reduce costs. This study considers the task-choices as activities and, in fact, cost drivers of the system.

For the estimation of the cost of task-choice i of task t ($\mathrm{C}_{t,i}$), three resource are taken into account: material, equipment, and labor. The cost of these resources for task-choice$_{t,i}$ is defined in the model as $Mat_{t,i}$, $Eqp_{t,i}$ and $Lbr_{t,i}$, respectively. Throughout the model, the costs occurring at task-choices are recorded in *Canadian dollar (CD)* and, therefore, $\mathrm{C}_{t,i}$ will be estimated in *CD*. As shown in equation (1), $\mathrm{C}_{t,i}$ is calculated by summing the material, equipment, and labor costs. The following explains how these resource costs are calculated for each personalized order.

$$C_{t,i} = Mat_{t,i} + Eqp_{t,i} + Lbr_{t,i} \tag{1}$$

Material Cost

Tasks might require material resource. As considered in the model, a material can be a raw or intermediate material, or a tool provided by a third-party manufacturing service. For a given type of material used in task-choice$_{t,i}$, the material cost is calculated using material usage in unit ($mu_{t,i}$) (e.g. 2 kg) and the price per unit ($mp_{t,i}$) (e.g. \$20/kg) obtained from suppliers (see equation (2)). The material usage of a task ($mu_{t,i}$) as well as the material unit price ($mp_{t,i}$) might change when the received order is different from the *default personalized order*; therefore, several parameters are considered to adapt equation (2) to different user inputs (i.e. "design effect" and "batch size effect" coefficients). The following provides more information on these parameters.

Design could affect material usage. For instance in a manufacturing process, when the design becomes more complex, more material might be required for the fabrication. For instance in glass micro-machining, a design with holes of different diameters requires several tools. Besides, extra tools might be required to etch a design with channels of different widths more quickly. In addition, in the same context, more complex designs might need more electrolyte to be machined properly. To consider the effect of design on material usage, $mue_{t,i}$ is considered in the model in order to record *the effect of design on material usage*. The parameter $mue_{t,i}$ is a user input to WebPMCS which can be provided by the fabricator, considering the features of the personalized design at hand. $mue_{t,i}$ is zero for a standard design, positive for more complex designs, and negative for simpler designs. As an example, if the fabrication specialist enters mue$_{t,i}$=0.15 for task-choice$_{t,i}$, the corresponding material usage shall increase by 15% for the design at hand; mue$_{t,i}$= - 0.15, on the other hand, decreases the material usage by 15%.

Design could also affect material purchasing fee in our model. As mentioned earlier, we have considered that materials could be provided by third-party manufacturing companies. For instance in glass micro-machining, we might outsource our “sample holder” to a third-party 3D printing company. It is possible that the supplier has higher fees for more complex sample holders, and this complexity could have been resulted from our more complex product design. In order to consider such scenarios, we have included $mpe_{t,i}$ as the effect of design on material unit price. The $mpe_{t,i}$ values are interpreted similar to $mue_{t,i}$.

Batch size can also affect material usage. If a task-choice has variable costs ($\mathrm{fv}_{t,i}$=1), the impact of batch size must be taken into consideration. In our model, $a_{t,i}$ is defined as the capacity of task-choice$_{t,i}$. When the batch size of the personalized order is more than the capacity of a task-choice, our model repeats the task-choice until the whole batch is fabricated. The value of $a_{t,i}$ is considered 1 (the task can handle one product at a time) unless one of the following conditions are true for task-choice$_{t,i}$:

- if the task-choice needs a tool but does not need equipment, $a_{t,i}$ is equal to *tool capacity*: the maximum batch size that the tool can process before replacement,
- if the task-choice needs equipment but does not need tooling, $a_{t,i}$ is equal to *equipment capacity*: the number of products that the equipment can process in parallel, and
- if task-choice$_{t,i}$ has both tooling and equipment, its capacity ($a_{t,i}$) will be the minimum of equipment and tool capacity.

For instance, the capacity of a given task that processes the workpiece and needs labor and raw material is considered 1 ($a_{t,i}$=1). Such task has to be repeated as the batch size (user input) becomes larger (e.g. a design with bs=5 requires 5 workpieces and the task has to be repeated 5 times). This effect is shown in equation (2) in form of “batch size effect”. As another example, if task-choice$_{t,i}$ has variable costs ($\mathrm{fv}_{t,i}$=1), its capacity is 15 ($\mathrm{a}_{t,i}$=15) and the batch size (user input) is 40 (bs=40), the batch size effect will be $1 + 1 \times (\cancelto{\lceil 2.67 \rceil = 3}{\lceil 40/(15) \rceil} - 1) = 3$; in other words, task-choice$_{t,i}$ shall be performed three times in this example.

$$Mat_{t,i} = mu_{t,i} \times mp_{t,i} \times \overbrace{(1 + mue_{t,i}) \times (1 + mpe_{t,i})}^{\text{design effect}} \times \overbrace{[1 + fv_{t,i} \times (\lceil bs/a_{t,i} \rceil - 1)]}^{\text{batch size effect}} \tag{2}$$

In equation (2), $mue_{t,i}$, $mpe_{t,i}$, and bs are user inputs while others are a priori set of parameters in the tool and could be used for all personalized orders. As seen in the equation, when we have a *default personalized order* ($mue_{t,i}$=0, $mpe_{t,i}$=0 $\forall$ t $\in$ T, i $\in$ I and bs=1), $Mat_{t,i} = mu_{t,i} \times mp_{t,i}$ regardless of the values of $fv_{t,i}$ and $a_{t,i}$. On the contrary, when the user inputs are not at their *default* values, $mue_{t,i}$, $mpe_{t,i}$, and bs modify the equation in such a way to consider the potential change of the material cost.

Equipment Cost

A task might need an equipment. The equipment cost is calculated using equation (3). It depends on equipment usage time in hour ($et_{t,i}$) and equipment (machining head) usage cost per hour ($ec_{t,i}$). Similar to material cost, the data corresponding to task-choices has been collected for a standard design and a batch size of 1 (the *default personalized order*); therefore, some additional parameters are needed to adjust equipment cost according to other possibilities of design and batch size.

More complex designs might require more machining time. For instance when the design becomes more complex, it might require several tools for the fabrication. Changing these tools during the fabrication, based on the design, takes some time and, at the end, a complex design could take more equipment usage time than a simple one. To address this, $ee_{t,i}$ is defined for task-choice$_{t,i}$ as *the effect of design on equipment usage time.* For instance $ee_{t,i}$=0.2 means that equipment usage time of task-choice$_{t,i}$ faces a 20% (0.2) increase (from its value in *default* user input) for the personalized order at hand. If $ee_{t,i}$= - 0.2, the equipment usage time shall be decreased by 20%.

Equipment cost must also adapt to batch sizes other than 1 (*default*). Batch size can only affect task-choices with variable costs ($\text{fv}_{t,i} = 1$). As an example for the batch size effect, if a task utilizes an equipment resource capable of processing 10 products and the task has no tooling (the tooling could be set in a prior task), the capacity of this task-choice ($a_{t,i}$) can be determined as 10. In that case, if a personalized order with bs=25 enters the system and passes towards this task-choice, the equipment is utilized three times (processing 10, 10, and 5 products in parallel) to accomplish the task ($\lceil 25/10 \rceil = \lceil 2.5 \rceil = 3$).

$$Eqp_{t,i} = \underbrace{et_{t,i} \times \overbrace{(1 + ee_{t,i})}^{\text{design effect}} \times \overbrace{[1 + fv_{t,i} \times (\lceil bs/a_{t,i} \rceil - 1)]}^{\text{batch size effect}}}_{\text{equipment usage time for different user inputs}} \times ec_{t,i} \tag{3}$$

As seen in equation (3), when the user inputs are at their default value ($ee_{t,i}$=0 $\forall$ t $\in$ T, i $\in$ I and bs=1), $Eqp_{t,i} = et_{t,i} \times ec_{t,i}$, no matter what the values of $fv_{t,i}$ and $a_{t,i}$ are. On the contrary, the equation will be modified in order to consider the potential cost change in case of more complex or simpler designs and/or larger batch sizes.

Labor Cost

Some tasks might require labor resource.The labor cost depends on the working time of the labor involved in task-choice$_{t,i}$ ($lt_{t,i}$) and the labor pay rate ($lp_{t,i}$). In addition, some parameters need to be defined in order to adapt the labor cost to different design complexities and batch sizes. Labor cost ($Lbr_{t,i}$) is calculated in equation (4).

Non-standard designs (more complex or simpler than our predefined standard design) might increase or decrease the labor working time. For instance, a complex design might require several tools to be used for its fabrication. In that case, the engineer might need to put more time on task “specifying appropriate tools” (that belongs to “Tooling” category) and/or “converting the design requirements to machining code” task (belonging to “Generate Machining Code” category). Similar to $mue_{t,i}$, $mpe_{t,i}$, and $ee_{t,i}$ for material and equipment resources, $le_{t,i}$ is defined for the labor resource as *the effect of design on labor working time*; $le_{t,i}$ is a user input and it modifies the labor working time of task-choice$_{t,i}$ based on the received personalized order.

Batch sizes larger than one (*default*) could increase the labor working time as well. As mentioned earlier, when task-choice$_{t,i}$ is required to handle more than its capacity, the task-choice is repeated in the model to meet the requirement. This increases labor working time if the given task-choice utilizes labor resource. As an example, the task of cleaning a fabricated workpiece might require equipment and labor resource. The operator spends some time to put products in the basket of a cleaning equipment (with a capacity of 10) and set the equipment. Considering 10 as the capacity of the task, the labor has to spend more time when, for instance, 20 products are to be processed by the task. In other words, the labor has to perform the setup of the cleaning facility twice. This doubles the labor working time and is considered in equation (4) at the "batch size effect" section of the formula.

$$Lbr_{t,i} = \underbrace{lt_{t,i} \times \overbrace{(1 + le_{t,i})}^{\text{design effect}} \times \overbrace{[1 + fv_{t,i} \times (\lceil bs/a_{t,i} \rceil - 1)]}^{\text{batch size effect}}}_{\text{labor working time for different user inputs}} \times lp_{t,i} \tag{4}$$

Equation (4) becomes $Lbr_{t,i} = lt_{t,i} \times lp_{t,i}$ for the default user input ($ee_{t,i}$=0 ∀ t ∈ T, i ∈ I and bs=1). "Design effect" and "batch size effect" parts of the equation ensure that the model adapts to other possibilities of the user input as well.

Total Cost

To summarize, the following shows how $C_{t,i}$, the total cost for task choice$_{t,i}$, is calculated for different personalized orders.

$$C_{t,i} = Mat_{t,i} + Eqp_{t,i} + Lbr_{t,i}$$

Where:

$$Mat_{t,i} = mu_{t,i} \times (1 + mue_{t,i}) \times mp_{t,i} \times (1 + mpe_{t,i}) \times [1 + fv_{t,i}(\lceil bs/a_{t,i} \rceil - 1)]$$

$$Eqp_{t,i} = et_{t,i} \times (1 + ee_{t,i}) \times [1 + fv_{t,i}(\lceil bs/a_{t,i} \rceil - 1)] \times ec_{t,i}$$

$$Lbr_{t,i} = lt_{t,i} \times (1 + le_{t,i}) \times [1 + fv_{t,i}(\lceil bs/a_{t,i} \rceil - 1)] \times lp_{t,i}$$

Personalized orders are recognized in WebPMCS by user inputs: bs, $mue_{t,i}$, $mpe_{t,i}$, $ee_{t,i}$, and $le_{t,i}$; ∀ t ∈ T and i ∈ I. Other parameters ($fv_{t,i}, a_{t,i}, mu_{t,i}, mp_{t,i}, et_{t,i}, ec_{t,i}, lt_{t,i}$, and $lp_{t,i}$) are a priori set for our tool and can be recorded once for the tasks in each manufacturing technology and be used for all personalized orders. For a given personalized order and for every task, the tool evaluates available task-choices and looks for task-choices with minimum $C_{t,i}$. The selected task-choices form the cost-effective fabrication route. Next section provides more detail on the decision process underlying WebPMCS tool.

3.3 Decision-Making Process

Figure 3.3 shows how WebPMCS uses the user inputs and the equations discussed in section 3.2 in order to find the most cost-effective fabrication route and report total production cost for each personalized order. We define the binary variable $s_{t,i}$ in the tool to specify whether or not a given task-choice is selected in the fabrication route. In other words, $s_{t,i}$ is equal to one if task-choice$_{t,i}$ is selected as the most cost-effective choice of task t. Among task choices of task t, only for one of them $s_{t,i}$=1 (at the end, only one of the choices is selected). In other words, $\sum_{i=1}^{I} s_{t,i} = 1; \forall t \in T$.

After a priori set of parameters ($fv_{t,i}, a_{t,i}, mu_{t,i}$, etc.) is provided to WebPMCS, it becomes enabled to select the most cost-effective fabrication route for different personalized orders. As seen in figure 3.3, the tool accepts *design effect* and *batch size* as inputs. These inputs represent the personalized order at hand and are entered by a fabrication specialist. Next, the tool selects a task from the process map, goes through its task-choices one by one, and estimates the corresponding costs. For every task, $s_{t,i}$=1 is recorded for the choice with minimum total cost (minimum $C_{t,i}$). Then, the cost of selected task-choices (those with $s_{t,i}$=1) is summed up and the most cost-effective fabrication route is formed. At the end, WebPMCS outputs the selected route along with its corresponding fabrication cost.

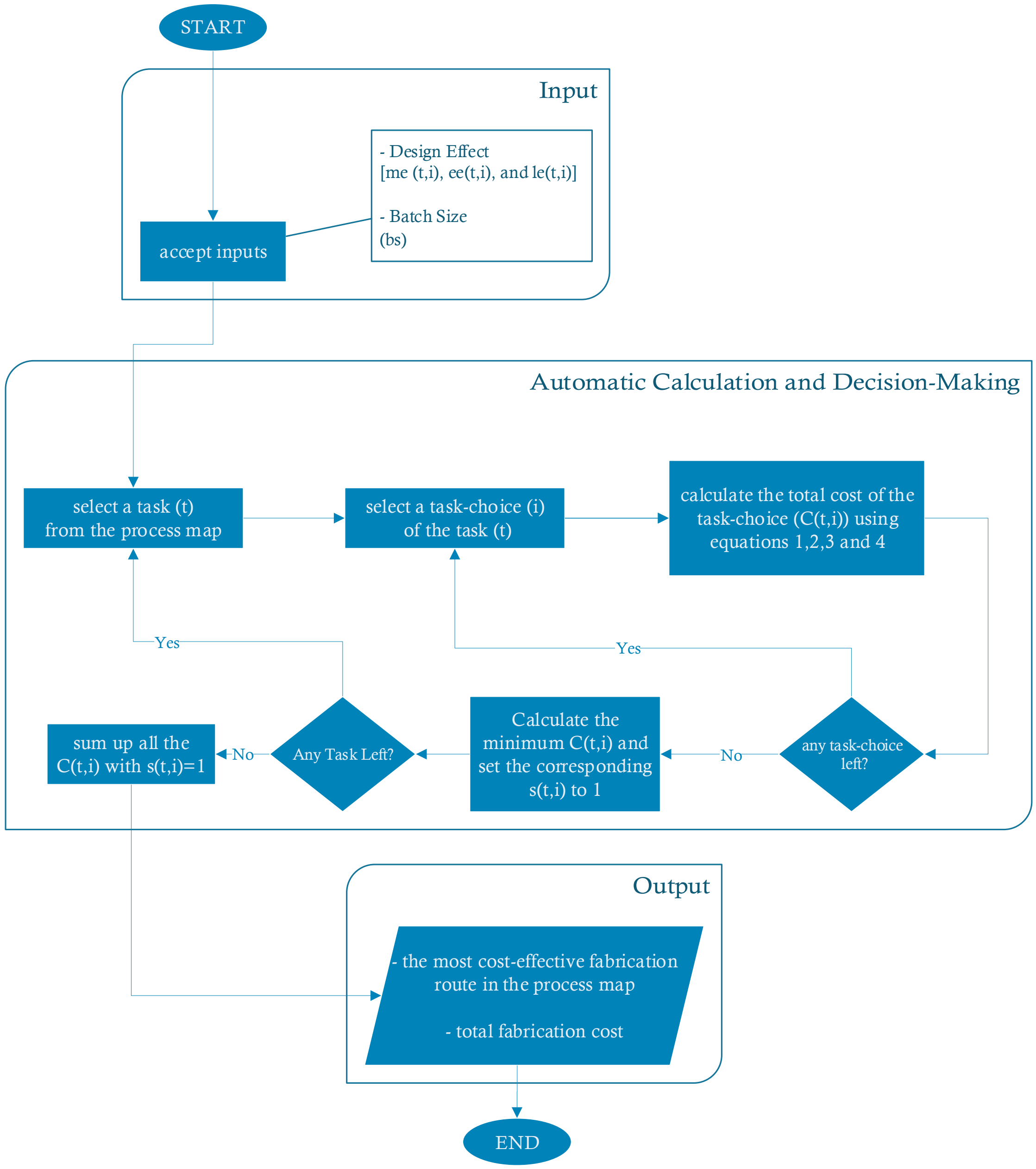

Figure 3.3: WebPMCS Decision-Making Process

Chapter 4

Implementation

As discussed in chapter 3, three steps are required in order to implement WebPMCS, including process mapping and task-choices, cost estimation of tasks, and decision-making routine. While the first step is technology-dependent, others are general steps and could be carried out quite similarly for different manufacturing technologies. When these steps are done and the technology-specific data is provided, WebPMCS will be ready to receive personalized orders. It will accept some *user inputs* for each order and provide the most cost-effective fabrication route accordingly.

For WebPMCS implementation, we developed a web-based application capable of accepting the required parameters and user inputs, performing cost estimation, and decision-making automatically. We designed the tool architecture and its components in such a way to perform process/resource selection using the methodology explained in chapter 3.

As our case-study, we utilized WebPMCS for Spark Assisted Chemical Engraving (SACE) process. We investigated SACE, mapped the process, and examined several of its task-choices. Then, we entered the data related to SACE tasks, task-choices, and *priori set of parameters* into WebPMCS database using the tool user interface. Finally, in order to show how the tool is used, we considered several SACE personalized orders and provided the *user inputs* for them.

This chapter starts by explaining how WebPMCS was developed. Next, it explains how the tool should be used for a given manufacturing technology. Finally, it explains how the tool is utilized, in practice, for the SACE process.

4.1 WebPMCS Architecture

WebPMCS is composed of two main components: the front-end, and the back-end. The front-end is the Graphical User Interface (GUI) where the tool shows the content and receives process-related data and user inputs. The back-end includes a database to store the relevant data, as well as some server-side code to perform process/resource selection and supply proper content to the GUI. Figure 4.1 shows how WebPMCS components are integrated. We utilized Django, a Python-based web framework, to make use of its built-in modules and automate some of the common necessary activities of web development. The following provides more detail for each component.

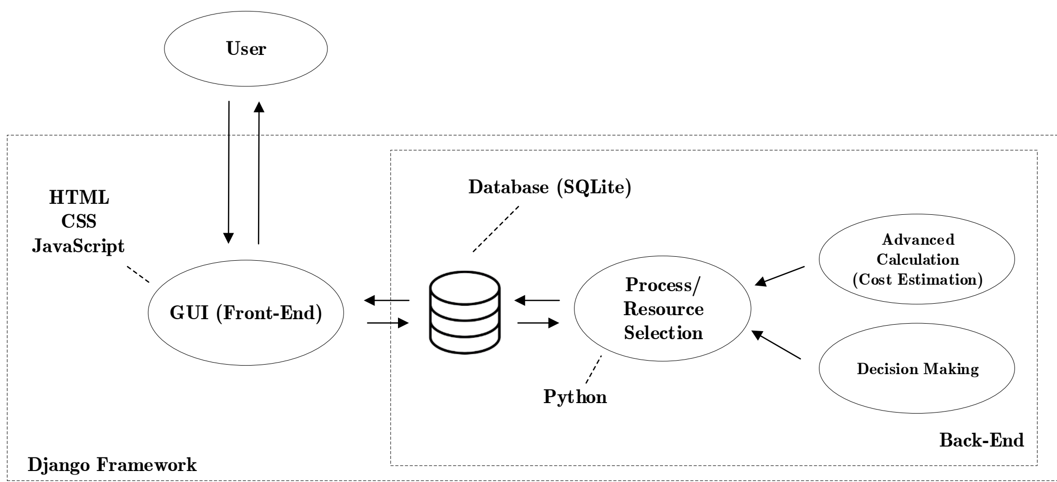

Figure 4.1: WebPMCS Architecture

Graphical User Interface (GUI)

The user can view and interact with the tool using the GUI (the front-end). The languages used in the front-end are HTML, CSS, and JavaScript. HTML is used to form the structure of web pages, CSS deals more with styling the pages, and JavaScript adds interactivity. We also use the Django template language for providing dynamic content to the GUI (e.g. showing the most up-to-date information on a web page). Using the GUI, the user can navigate through the tool, provide required parameters/user inputs, and observe the corresponding results/reports.

Database

The data related to the manufacturing technologies, tasks, task-choices, resources, parameters and most of the user inputs are stored in and accessed from a database. We have used SQLite, a relational database, at the back-end. Figure 4.2 shows the database relational schema. It illustrates the database tables and the relationships between them. The title and the columns of each table is shown in this figure. For instance, the *Manufacturing Technology* table has three columns: *id*, *name*, and *acronym.* The value types of columns are shown in front of them in the figure (e.g. *name* has the type of *character* (CHAR) in the database). In addition, the type of each column (primary key, required, non-required etc.) is shown on their left. For instance, the field *name* is required for the *Manufacturing Technology* table but the field *acronym* is not. The connecting lines between tables show the relationships. The symbols for the types of relationships are illustrated in the figure legend. As an example, *high-level generic tasks* which were considered as categories (see section 3.1) are recorded in the *Category* table. Therefore, we expect each category to have one to many tasks (i.e. *last-level tasks*). This is equivalent to a one-to-many relationship, as we see between the *Category* and *Task* tables (see the relationship line in the figure).

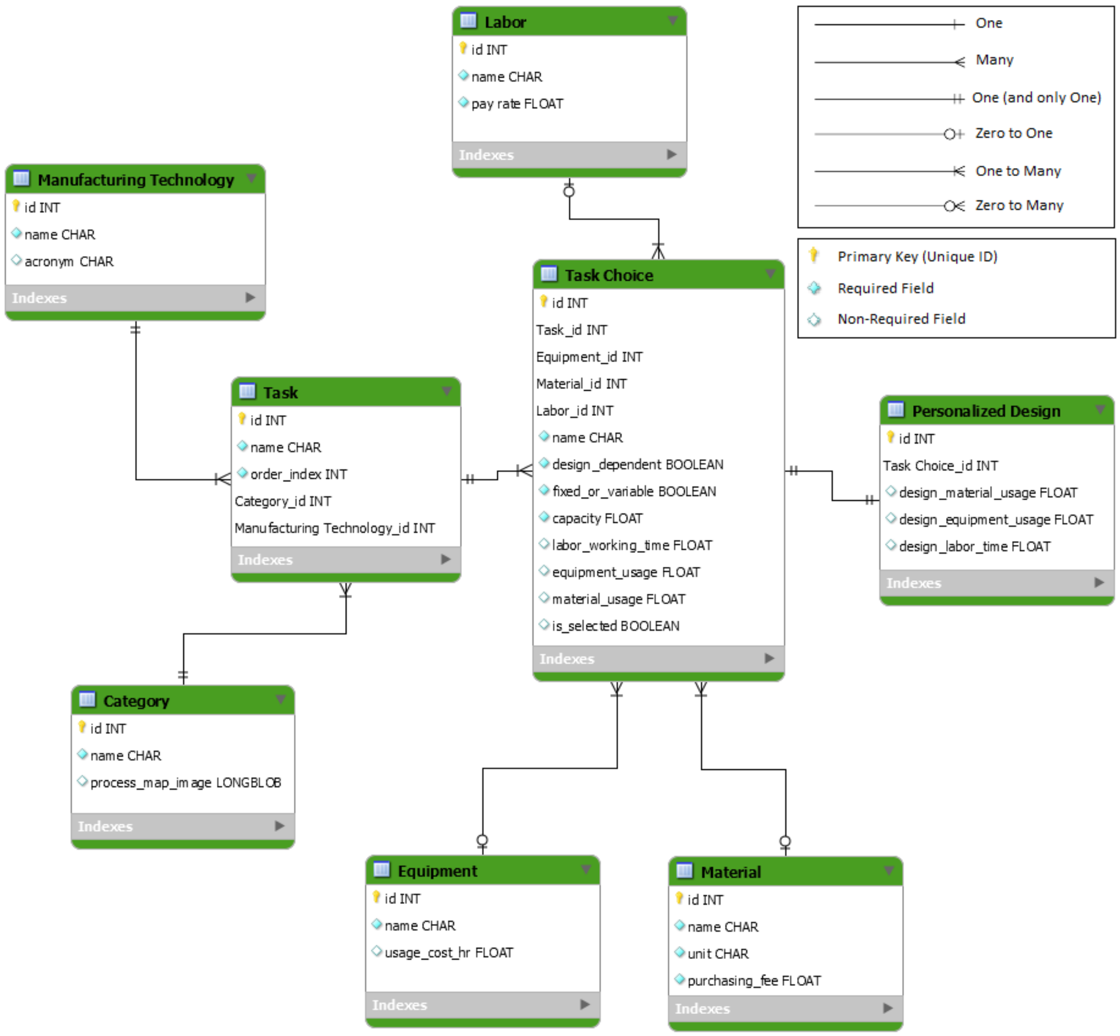

Figure 4.2: Database - Relational Schema

Django framework has a default object-relational mapping layer (ORM) which we have used to interact with our SQLite database. We used Django ORM to create the tables, specify relationships, and query the data, all using Python code.

Process/Resource Selection

As it can be seen in figure 4.1, the *process/resource selection* includes *advanced calculation* and *decision making*. The former uses the cost-estimation model discussed in section 3.2 to calculate the cost for every task-choice based on the user inputs and the information available in the database. The latter selects the most cost-effective task-choices based on the estimated cost (see section 3.3). The cost estimation equations are programmed in Python.

4.2 WebPMCS

This section explains how WebPMCS can be used for a particular manufacturing process. Figure 4.3 shows the home page of WebPMCS. There are buttons on the navigation bar (navbar) for different purposes.

Figure 4.3: WebPMCS Home Page

The "Admin" button on the navbar directs to a well featured admin panel (see Figure 4.4). This panel is a built-in feature of Django framework which has been customized in this study for WebPMCS. In this panel, data could be added/modified, and different users with different access permissions could be defined (e.g. some users can view certain tables but are not allowed to modify or delete them).

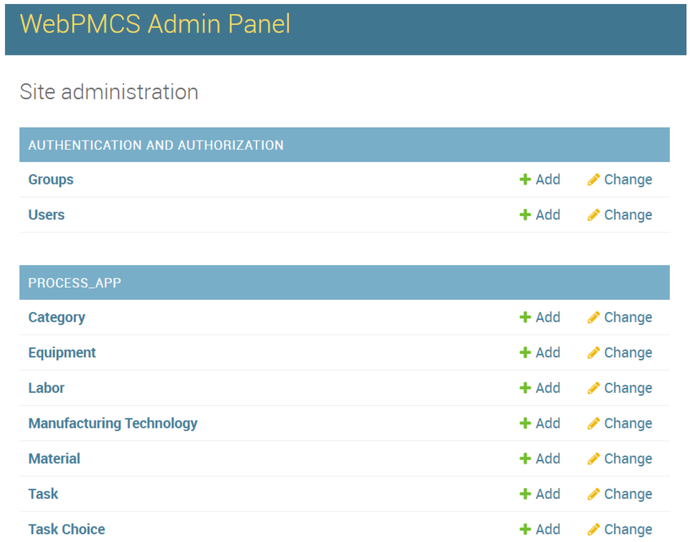

Figure 4.4: WebPMCS Admin Panel

The first step for using WebPMCS is entering the technology-specific data into the tool from the admin panel (figure 4.2 shows the list of database tables). We fill the tables in the admin panel based on the given manufacturing technology. Figure 4.5 shows how, for example, different manufacturing technologies and tasks can be added. It is noteworthy that the *Personalized Design* table (see figure 4.2) is not accessible from the admin panel. This table will be filled later automatically when user inputs are provided using the GUI for a specific personalized design.

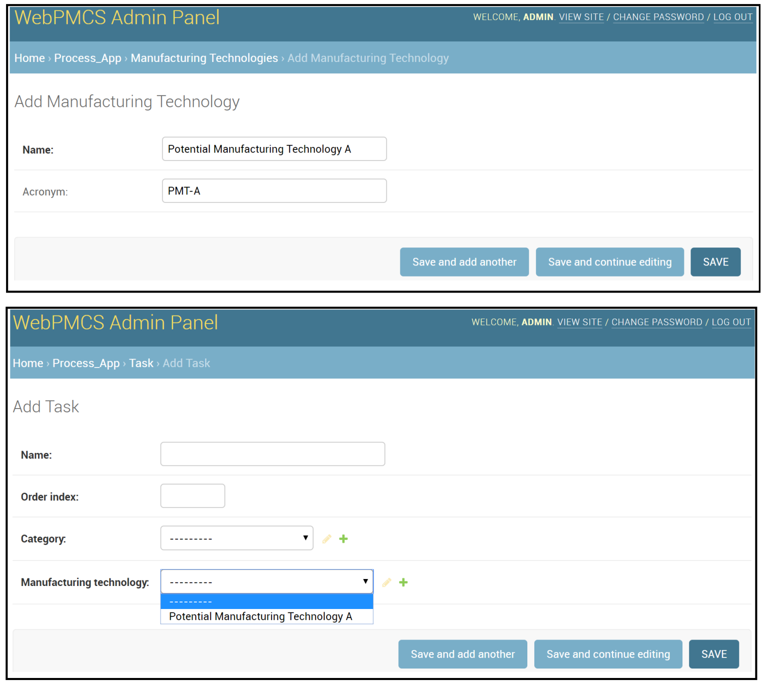

Figure 4.5: Entering Data from Admin Panel

The next button on the navbar is "Report". It directs to a page with a list of available manufacturing technologies, which then directs to different charts automatically drawn with the data of the manufacturing process. We will illustrate these charts for our case-study in the "Experimental Results" chapter.

The "Process & Resource Selection" button on the navbar directs the user to a page with a list of available manufacturing technologies (see Figure 4.6).

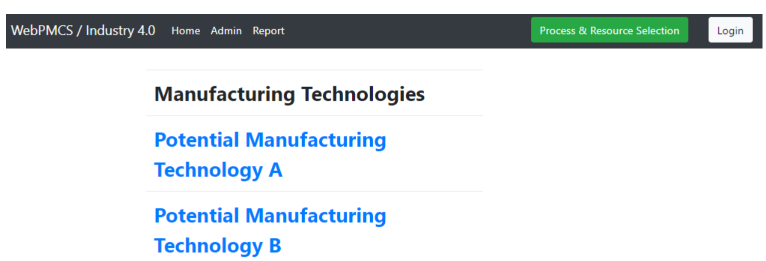

Figure 4.6: WebPMCS - List of Manufacturing Technologies

By selecting the manufacturing technology for fulfilling the personalized order, the user is directed to a new page that shows the process map at the top and the tasks associated with the selected manufacturing process at the bottom. The user can see the detailed steps of each task in the generic process map by clicking on the associated button (see Figure 4.7). The user can also see the list of task-choices by clicking on each task.

Starting by a personalized order, the user goes through all task-choices and enters the appropriate value for $me_{t,i}$, $ee_{t,i}$, and $le_{t,i}$ in addition to the batch size. Afterwards, the user presses the "Decide" button that runs a Python code at the back-end of WebPMCS. It, then, directs the user to a new page where all the task-choices that are part of the most cost-effective fabrication route are listed.

Figure 4.7: WebPMCS - DeciInteractive Process Map for Each Manufacturing Technology

4.3 Case-Study

Spark Assisted Chemical Engraving (SACE) is considered as our case-study. A brief introduction to SACE technology in addition to the motivation behind choosing it as our case-study are provided as follows. We also elaborate on how the WebPMCS is adapted to the SACE manufacturing process.

Spark Assisted Chemical Engraving

Spark Assisted Chemical Engraving (SACE) (also known as Micro-electrochemical discharge machining (ECDM)) is a hybrid technology combining high machining rates of thermal processes with precision of chemical methods. SACE machines non-conductive materials by applying voltage between the tool-electrode and counter-electrode which are both dipped into an electrolyte solution (see Figure 4.8). At voltages higher than a critical voltage, bubbles around the tool come together and form a gas film. Sparks occur through the gas film and local etching happens by bombardment of discharges and thermally-promoted material removing (Wüthrich & Ziki, 2009). SACE is capable of machining holes of up to 2000 μm in diameter and producing high aspect rations (up to >10) while providing relatively high transparency and smoothness of machined surfaces ($R_a = 0.13\mu m$) (Wüthrich & Hof, 2006).

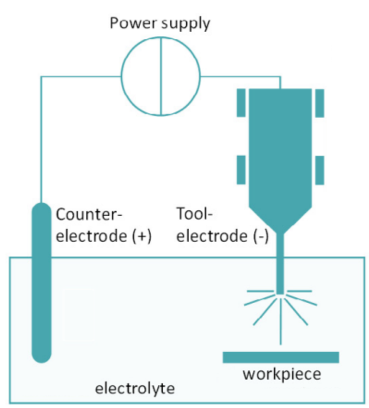

Figure 4.8: SACE machining principle (adapted from Hof and Wüthrich (2017))

SACE is capable of machining personalized complex products from CAD (Computer-Aided Design) files. It also involves low tooling expenses. These features make this process suitable for personalization. Figure 4.9 shows several examples of personalized fabrication using SACE in medical, watch, and electronics industries as well as rapid prototyping. Due to the SACE potentials for mass personalization and our access to the data related to this technology, we selected it as our case-study.

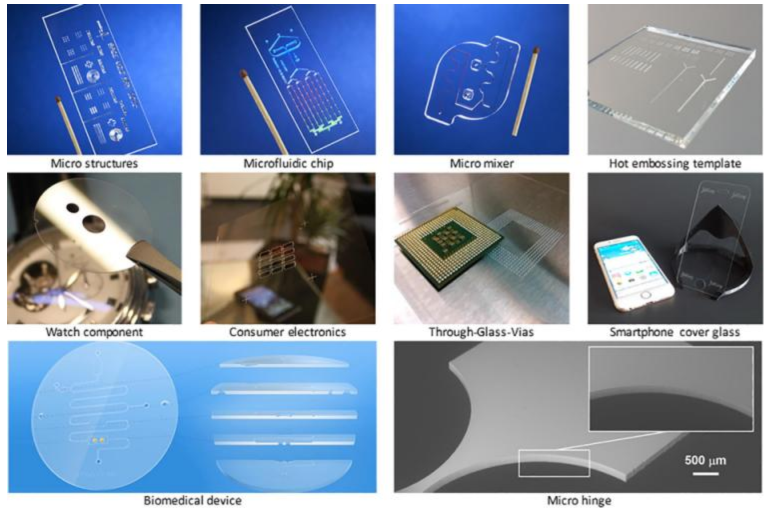

Figure 4.9: Examples of personalized fabrication using SACE process (Hof & Wüthrich, 2017)

After a product design is received in form of a CAD file, we can fabricate the product using SACE process in several steps. First, the tool-electrode, electrolyte and sample holder are specified and provided. Meanwhile, the CAD file of the design is converted to a CAM (Computer-Aided Manufacturing) file which will be used to control the movement of the tool-electrode in fabrication. Performing the machine setup is the next step. Finally, the workpiece is fabricated and cleaned. The following provides more detail on the SACE process and how it was included in WebPMCS.

Adapting WebPMCS to the SACE process

This section focuses on setting WebPMCS to our case-study, SACE manufacturing technology. We will discuss mapping the process, defining task-choices, specifying the priori set of parameters, and providing user inputs related to personalized orders.

SACE Process Mappings and Task-Choices

As explained earlier in section 3.1, process mapping starts with a generic process map. It gets broken down further in order to reach last-level tasks. Figures 4.10 and 4.11 show the result of process mapping for SACE process. All the tasks with a quarter of a black circle at their top right corner are last-level tasks which we consider as the *tasks* of SACE process.

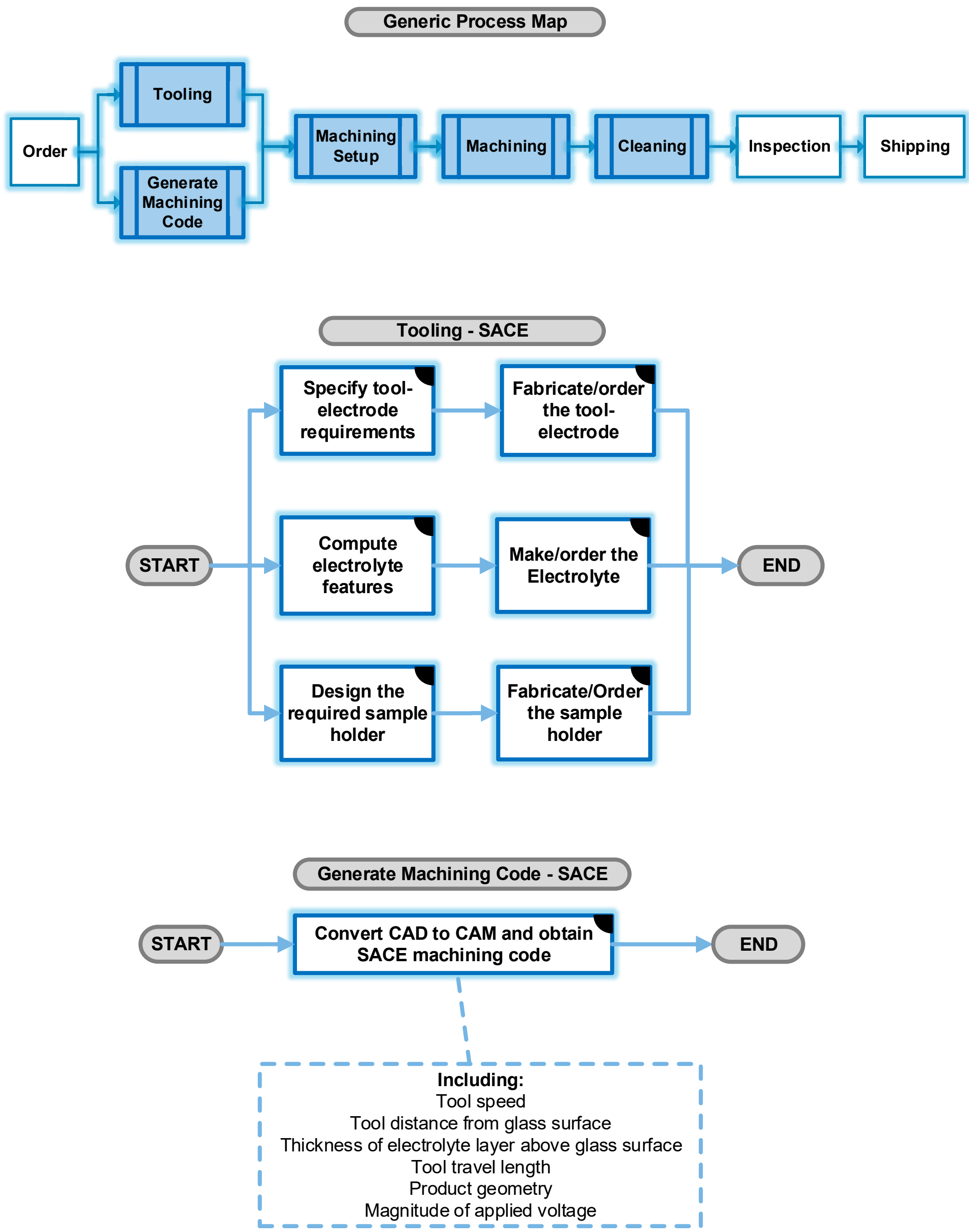

Figure 4.10: SACE Process Map - Part 1 of 2

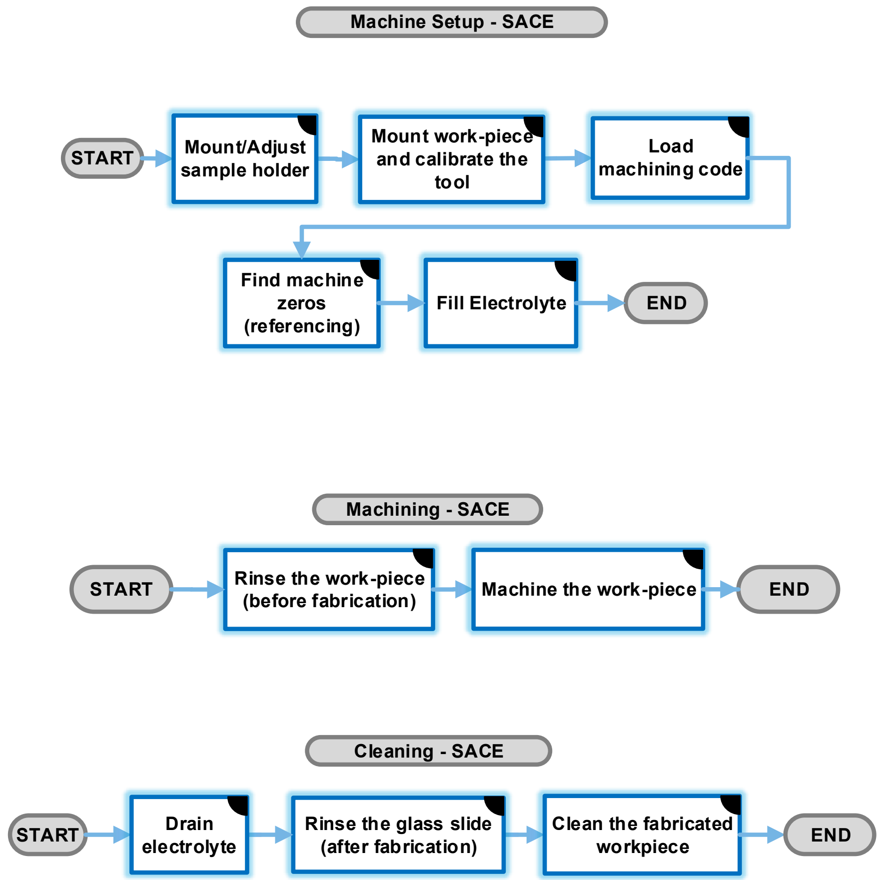

Figure 4.11: SACE Process Map - Part 2 of 2

We must consider one to many choices for every task in the process map. The first three columns of table 4.1 show some of SACE possible task-choices that we considered in our case-study. In practice, the decision making will be only done for tasks with two or more choices. As mentioned in chapter 3, a set of parameters must be provided to WebPMCS. The following provides the values specified for SACE process.

Set of Parameters

Personalized orders are customer-specific batches of unique designs, and the values of WebPMCS parameters depend on them (batch size and design). Therefore, we consider fabricating one ($bs = 1$) *standard design* as our *default personalized order* and specify the parameters accordingly (a *standard design* could be any design specified by a production expert). We then see this *default* as our reference point for other personalized orders and include related *user inputs* for each order to adapt the tool. In this section, we investigate three designs (the standard design along with two other personalized designs) and provide the parameters/user-inputs for them. Considering these three designs will also help us in the next chapter for validating the tool and performing analysis.

The *standard* design and the two personalized designs considered for glass-micro machining using SACE process are shown in figure 4.12. The *standard* design has one 2mm (width) channel and several 1mm (width) channels, all with the same depth (1mm). Design A has one straight 3mm (width) channel with the depth of 1mm. Design B, on the other hand, has a 1mm (width) channel and four 2mm (diameter) holes with the depth of 1mm, in addition to four 3mm (diameter) through holes with the depth of 4mm. Considering all the dimensions of design A, design B, and the *standard design*, the volume of the removed glass (etching volume) is identical for the three of them.

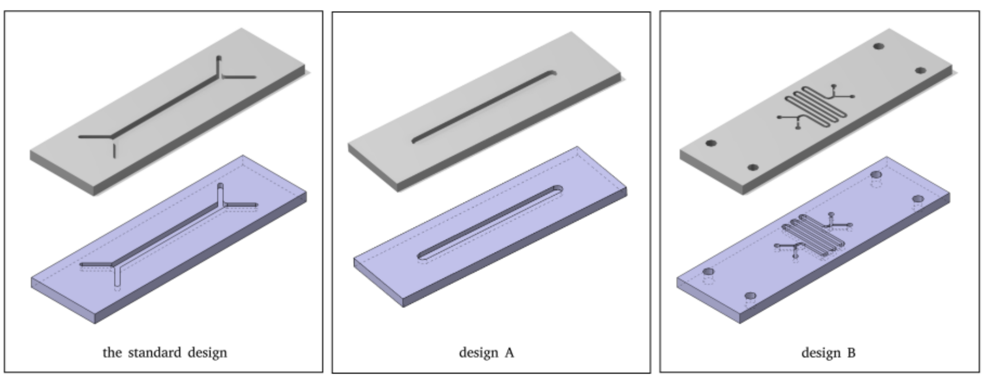

Figure 4.12: Three SACE designs

In SACE process, design features such as dimension, required machining mode (e.g. drilling and etching), aspect ratio, taper angle, and required surface quality could determine how *complex* a design is. For example, designs with more varied dimensions or demanding aspect ratios are considered more *complex* as their fabrication could be more difficult/time-consuming. Comparing design A, design B, and the standard design, we consider that their difference is only in *variety of dimension* and *the number of required machining modes*. As a comparative term for their complexity, we call them *simple*, *complex*, and *standard* designs, respectively (see figure 4.13).

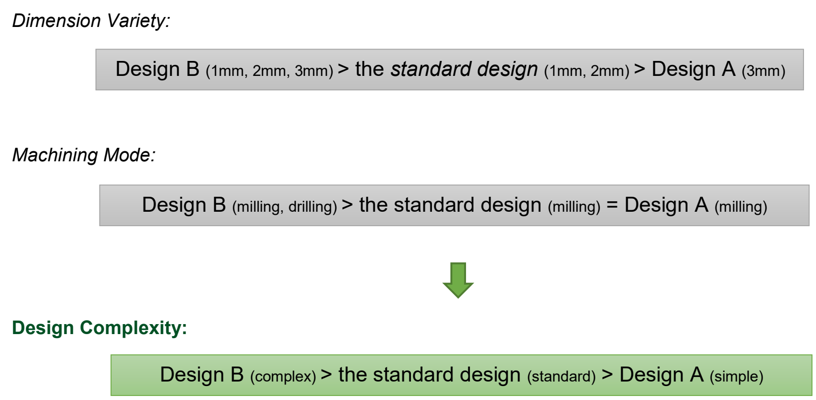

Figure 4.13: comparison of design A and B with the *standard design*

As mentioned in section 3.2, it is usually required or more cost-effective for more complex designs to use multiple tool-electrodes. For example, for the *standard* design, it will highly reduce the machining time if we use a 1mm tool-electrode for the 1mm channel and a 2mm tool-electrode for the 2mm channel, versus fabricating with only a 1mm tool-electrode. Moreover, for the *complex* design, it is required to use two tool-electrodes (2mm and 3mm) for appropriate machining of the existing holes with different diameters; we should also use a 1mm tool-electrode to etch the 1mm channel. SACE is an expensive equipment and we considered to take this multi-tool approach in order to reduce the fabrication time. In our consideration, an automatic tool changer takes care of the multiple tool-electrodes needed for machining the *standard* and *complex* designs. This tool changer moves as per the machining code instructions which comes from the main motor of the machine. During fabrication, one tool-electrode will be used at a time. Figure 4.14 shows the tool changer set for a *complex* design. As shown in the figure, in our definition, a *machining head* includes the main motor which handles fabrication steps and executes the machining code. It is possible to arrange several *machining heads* beside each other to make a multi-head machine. A *tool-electrode head* refers to the tool changer with its tool-electrodes. Each *machining head* can include one or several *tool-electrode heads*. In the following, we provide the parameters to WebPMCS considering that the SACE equipment has a single machining head which includes a single tool-electrode head (as shown in figure 4.14).

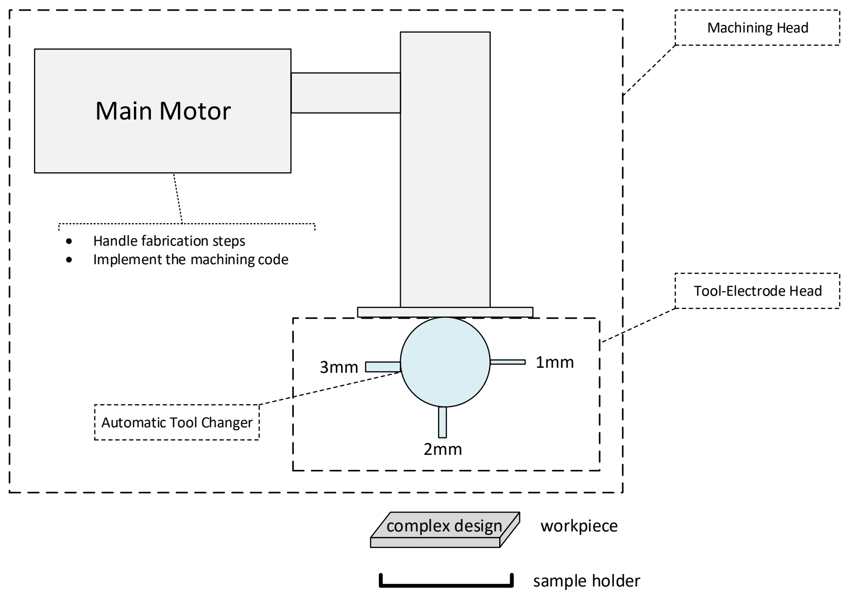

Figure 4.14: SACE fabrication using an automatic tool changer

Table 4.1 shows WebPMCS parameters for the three designs. The *standard design* is considered for providing the *priori set of parameters*. These parameters will be used for all the orders that WebPMS will receive. Design A and B, however, are two potential personalized orders which we specified the *user inputs* for them. The *standard design* is the reference of all user inputs. In other words, if WebPMCS receives a design identical to the *standard design* in terms of features, all the corresponding design-related user inputs will be zero for that design.

As it can be seen in table 4.1, the *fabricate the tool-electrode from Stainless Steel with mechanical grinding* task-choice has variable costs ($fv_{t,i}$=1), can handle up to 5 products (the tool-electrode needs replacement after 5 fabrication) ($a_{t,i}$=5), and takes 12 minutes (0.2 hour) of the mechanical grinding equipment ($et_{t,i}$=0.2) which has a \$4 (CAD) per hour rate ($ec_{t,i}$=4). It also takes 18 minutes of labor resource ($lt_{t,i}$=0.3) that is paid \$65 per hour

($lp_{t,i}$=65) and needs two units of material (Stainless Steel bars)($mu_{t,i}$=2) which are priced at \$0.15 each ($mp_{t,i}$=0.15). The *user inputs* are recorded in form of float numbers (0.2 means 20% increase). For instance, the task-choice *convert the personalized CAD to CAM and obtain machining code* faces a 50% increase in labor time for the complex design (design B) compared to the standard design. This is because of the extra features that the engineer needs to include in order to generate an appropriate machining code. For instance, the machining code should include different tool-electrodes used to machine different sections. For the same reason, the labor time for this task-choice decreases by 40% for a simple design (design A). Another example is the *fabricate the tool-electrode from Tungsten with mechanical grinding* task-choice; the number of needed tool-electrodes increase in design B (complex); therefore, material usage, equipment usage, and labor time have increased by 50%, 50%, and 40%, respectively. The task-choice *machine the work-piece using SACE technology* is another example where the equipment cost has increased for the complex design. That is because the design has a longer trajectory than the standard design.

We consider the three designs discussed so far (design A, design B, and the *standard design*) with three batch sizes (10, 100, and 1000). It creates nine potential personalized orders (see figure 4.15). Having these orders, we validate WebPMCS functionality and obtain the most cost-effective fabrication route for each order in the following chapter.

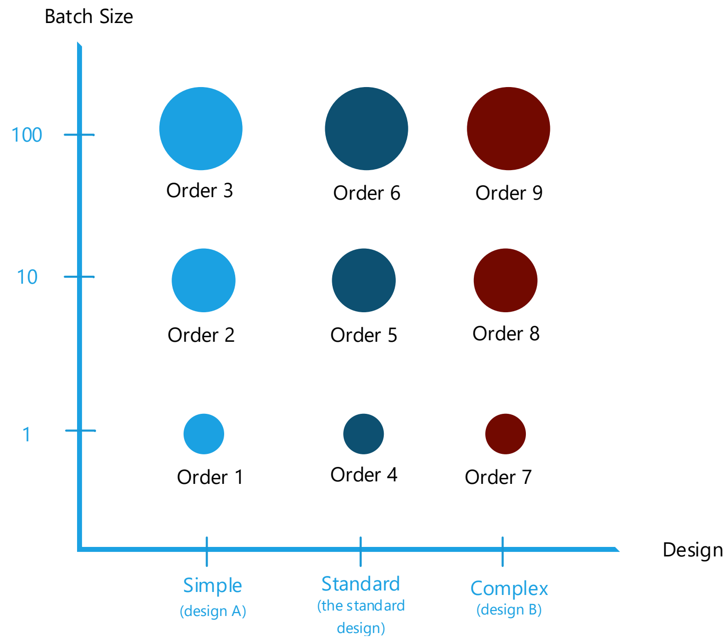

Figure 4.15: Nine potential personalized orders

Table 4.1: SACE tasks, considered task-choices, and the corresponding set of parameters

Category	Task	Task-Choice	The priori set of parameters (for the standard design and batch size = 1)								User inputs for design A and batch size = 1				User inputs for design B and batch size = 1			
			$fv_{t,i}$ fixed/variable (binary; fixed: 0)	$a_{t,i}$ capacity	$et_{t,i}$ equipment time (hr)	$ec_{t,i}$ equipment cost ($)	$lt_{t,i}$ labor time (hr)	$lp_{t,i}$ labor price ($)	$mu_{t,i}$ material usage	$mp_{t,i}$ material price ($)	$mue_{t,i}$ design effect-material usage (%)	$mpe_{t,i}$ design effect-material price (%)	$ee_{t,i}$ design effect-equipment (%)	$le_{t,i}$ design effect-labor (%)	$mue_{t,i}$ design effect-material usage (%)	$mpe_{t,i}$ design effect-material price (%)	$ee_{t,i}$ design effect-equipment (%)	$le_{t,i}$ design effect-labor (%)
Tooling	specify tool-electrode requirements	specify the tool-electrode for the personalized order	0	-	0	0	0.1	65	0	0	0	0	0	-0.2	0	0	0	0.5
	fabricate/order the tool-electrode*	fabricate the tool-electrode from Stainless Steel with mechanical grinding	1	5	0.25	4	0.2	65	2	0.2	-0.5	0	-0.3	-0.25	0.5	0	0.3	0.25
		fabricate the tool-electrode from Tungsten with mechanical grinding	1	15	0.25	4	0.2	65	2	0.3	-0.5	0	-0.3	-0.25	0.5	0	0.3	0.25
		order the required tool-electrode in Stainless Steel from supplier A	1	5	0	0	0.1	32	2	6	-0.5	0	0	0	0.5	0	0	0
		order the required tool-electrode in Stainless Steel from supplier B	1	7	0	0	0.1	32	2	5.75	-0.5	0	0	0	0.5	0	0	0
		order the required tool-electrode in Tungsten from supplier C	1	17	0	0	0.1	32	2	7.5	-0.5	0	0	0	0.5	0	0	0
		order the required tool-electrode in Tungsten from supplier D	1	15	0	0	0.1	32	2	7.25	-0.5	0	0	0	0.5	0	0	0
	compute electrolyte features	compute electrolyte features for the personalized order	0	-	0	0	0.2	65	0	0	0	0	0	-0.2	0	0	0	0.3
	make/order the electrolyte*	order and receive NaOH 20% electrolyte solution	1	1	0	0	0.1	32	4	4.25	-0.4	0	0	0	0.5	0	0	0
		order and receive KOH 20% electrolyte solution	1	1	0	0	0.1	32	4	5	-0.4	0	0	0	0.5	0	0	0
		order NaOH electrolyte powder and prepare a 20% solution	1	1	0	0	0.3	32	0.8	14.7	-0.4	0	0	-0.1	0.5	0	0	0.1
		order KOH electrolyte powder and prepare a 20% solution	1	1	0	0	0.3	32	0.8	22	-0.4	0	0	-0.1	0.5	0	0	0.1
	design the required sample holder	design the sample holder based on the part	0	-	0	0	0.5	65	0	0	0	0	0	-0.1	0	0	0	0.15
	fabricate/order the sample holder*	fabricate the sample holder in-house using 3D printing and ABC material	1	10	0.7	35	0.2	32	0.02	31.5	-0.1	0	0	0	0.15	0	0	0
		outsource the required sample holder from a supplier	1	10	0	0	0.1	32	1	40	0	-0.3	0	0	0	0.2	0	0
Generate machining code	converting CAD to CAM and obtaining SACE machining code	convert the personalized CAD to CAM and obtain the machining code	0	-	0	0	0.5	65	0	0	0	0	0	-0.4	0	0	0	0.5
Machine setup	mount/adjust sample holder	mount the sample holder and adjust its position and angle	1	1	0	0	0.1	32	0	0	0	0	0	0	0	0	0	0
	Mount the work-piece and calibrate the tool-electrode	mount the workpiece, adjust the tool/workpiece angle, and eliminate tool run-out	1	1	0	0	0.25	32	0	0	0	0	0	-0.2	0	0	0	0.15
	load machining code	load the machining code into SACE machine	0	-	0	0	0.1	32	0	0	0	0	0	0	0	0	0	0
	find machine zeros (referencing)	find machine zeros and record in the machining code	1	1	0	0	0.05	32	0	0	0	0	0	0	0	0	0	0
	fill electrolyte	fill electrolyte into the container	1	1	0	0	0.05	32	0	0	0	0	0	0	0	0	0	0
Machining	rinse the work-piece (before fabrication)	rinse the work-piece (before fabrication) manually	1	1	0	0	0.05	32	1	0.2	0	0	0	0	0	0	0	0
	machine the work-piece	machine the work-piece using SACE technology	1	1	1.5	200	0.25	32	0	0	0	0	-0.1	0	0	0	0.2	0
Cleaning	drain electrolyte	let the electrolyte drain in the container	1	1	0	0	0.1	32	0	0	0	0	0	0	0	0	0	0
	rinse the glass slide (after fabrication)	rinse the machined glass slide manually	1	1	0	0	0.05	32	0	0	0	0	0	-0.1	0	0	0	0.3
	clean the fabricated workpiece	clean the fabricated workpiece using a cleaning facility	1	20	0.1	15	0.05	32	0	0	0	0	-0.2	0	0	0	0.3	0

* Tasks with two or more considered task-choices

Chapter 5

Experimental Results

This chapter starts by validating WebPMCS using cost and sensitivity analyses. We make sure that WebPMCS is implemented appropriately and works as expected. Then, we go through selecting the most cost-effective fabrication route for different personalized orders. Finally, with the insight provided by WebPMCS report, we provide and validate a suggestion to improve SACE process for mass personalization.

5.1 Validating WebPMCS

In this section, we validate the tool by considering a single fabrication route for all personalized orders (there is no need for process/resource selection). In fact, among available alternatives (see table 4.1), we select to "fabricate the tool-electrode from Stainless Steel with mechanical grinding", "order and receive NaOH 20% electrolyte solution", and "fabricate the sample holder in-house using 3D printing and ABC material". We will report the production costs and the changes in the cost under different scenarios accordingly.

Figure 5.1 shows the cost distribution of total production cost, labor cost, material cost, and equipment cost for the aforementioned task categories. As seen in chart A, the *machining* category causes 63.8%, the highest percentage, of the total production cost. This is because SACE, our main equipment, is a quite expensive machine. After the *machining* category, *tooling* (24.3%) is the most expensive category. We expected this as the *tooling* tasks consists of six labor-intensive sub-tasks, as seen in table 4.1. We have also *generate machining code*, *machining set-up*, and *cleaning* categories which make 6.7%, 3.6%, and 1.6% of the total cost, respectively. As expected, these three categories are not very costly for the SACE process. Generating the machining code using CAD (Computer-Aided Design) file is not very time-consuming and costly since the engineer involved in the task gets assistance from a computer software and the code will be generated almost automatically. In addition, SACE is an advanced manufacturing technology and *machining set-up* is not very costly for that. Many of the machining settings are included in the machining code and SACE does not need many extra set-ups for machining. Finally, *cleaning* is quite inexpensive for glass micro-machining using SACE. It is quite easy to clean the flat glass slide before fabrication. Further, electrolyte is pumped and flowed when the glass is being machined which removes the etched glass particles hence cleaning the workpiece after the fabrication will not be much more difficult either. As illustrated in chart B, *labor* cost is caused mostly at the *tooling* category (53%). In other words, we have the most *labor* involvement in this category. This result is expected for SACE process. Specifying/making the appropriate tooling for each personalized order is a sensitive task which needs an engineer familiar with the process. Besides, we have selected to *fabricate* the tool-electrode and the sample-holder in-house, which needs extra labor involvement in this category. Next, the *generate machining code* category causes 23.1% of the labor cost. This is the time that the engineer should spend in order to apply the settings using a CAD/CAM software and generate the machining code. *Machining set-up* causes 12.5% of SACE labor cost as expected; the tasks of this category all need an operator (e.g. for mounting the workpiece). The *machining* category has also some labor cost (6.8%) which is related to the time that operator rinses the glass slide before fabrication and inspects SACE periodically during its operation. Lastly, chart B shows that *cleaning* category causes 4.5% of labor cost which is associated with the time that the operator rinse and clean the workpiece after fabrication. As expected, chart C shows that *material cost* happens only in *tooling* and *machining* categories of SACE process. This relates to the materials such as electrolyte, sample holder, and tool-electrode (*tooling* category) as well as glass slide (*machining* category). Chart D shows where *equipment cost* happens. As we could expect, while *machining* makes 91.8% of the equipment cost (due to the high price of SACE machine), *tooling* causes 7.7% (mechanical grinder and 3D printer) and *cleaning* only 0.5% (cleaning facility) of the equipment cost.

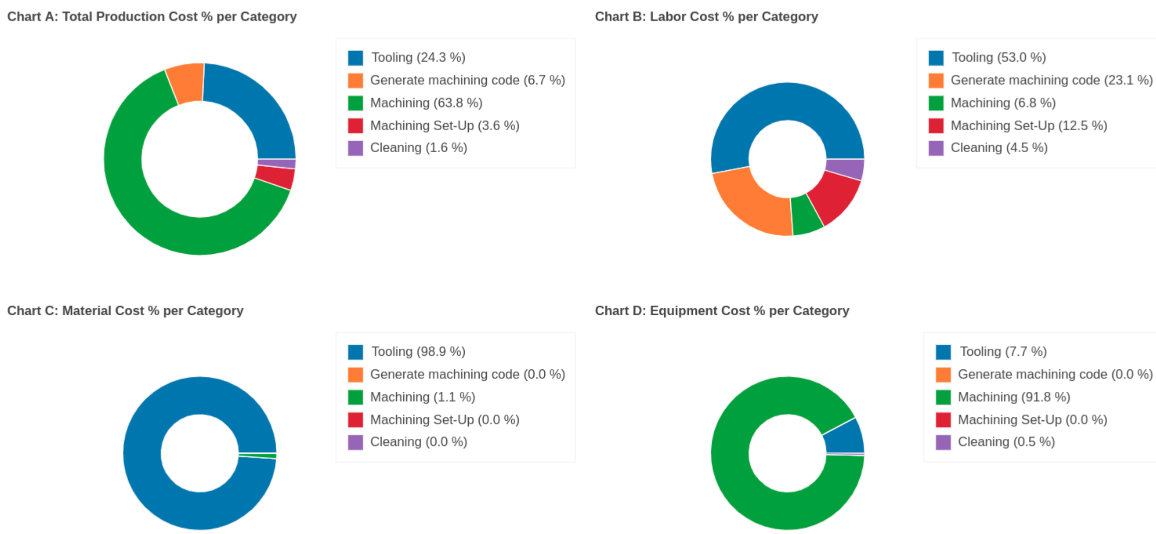

Figure 5.1: Cost per Category (standard design; batch size = 1)

Figure 5.2 shows the cost distribution per resource. The results confirm the ones provided in figure 5.1. We can see that in overall (chart A) *equipment* cost has the highest percentage. This is expected due to the high cost of SACE machine, which makes the equipment cost even higher than the total labor cost. We can also see the dominant resource for each category. *Labor* for *tooling* (chart B), *labor* for *generate machining code* (chart C), *equipment* for *machining cost* (chart D), *labor* for *machining set-up* (chart E), and *labor* for *cleaning* (chart F) constitute the highest resource cost. This is expected for SACE since material cost is quite low for glass micro-machining. Looking at the percentage values of the charts also helped us make sure that WebPMCS is working as expected.

Figure 5.2: Cost per Resource (standard design; batch size = 1)

Afterwards, we performed a set of sensitivity analysis tests to investigate the impact of different resources on production cost. Figure 5.3 shows the impact of labor pay rate increase on the total production cost as well as the cost of each task category. As expected, the production cost increase as the labor pay rate is augmented. Among the lines associated with task categories, *tooling* has the sharpest slope. We expected this result since most of the *labor cost* occurs in the *tooling* category (see figure 5.1: chart B) and the relationship between labor pay rate and production cost is linear for a given design and batch size (see equations (1) and (4) in section 3.2).

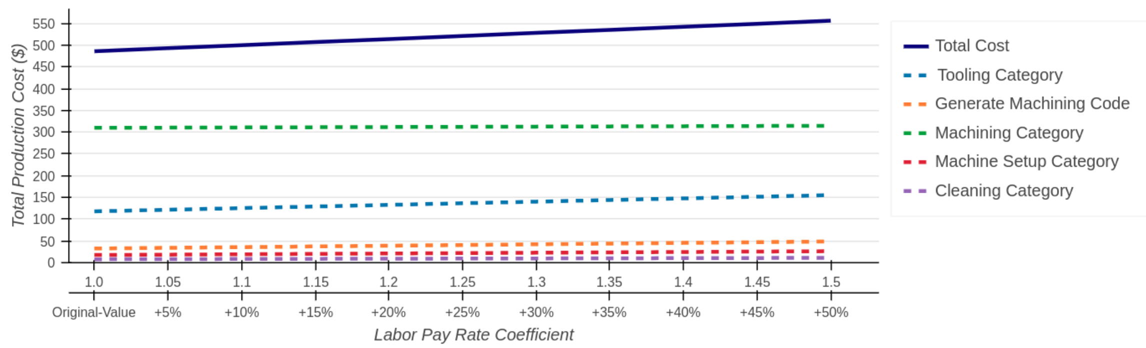

Figure 5.3: The impact of labor cost coefficient on production cost (standard design; batch size = 1)

Figure 5.4 shows the impact of material purchasing fee on production cost of different task categories. While the cost of *cleaning*, *generate machining code*, and *machine setup* do not increase with the material purchasing fee, we can see an increase in *tooling* and *machining* categories. This is expected since the former categories do not include any material (see figure 5.1: chart C). We can also see that the slope of line charts is not sharp at all. This is expected since material cost makes a small portion of the production cost (see figure 5.2: charts A-F). The lines are also linear as we expected from equations (1) and (2) in section 3.2.

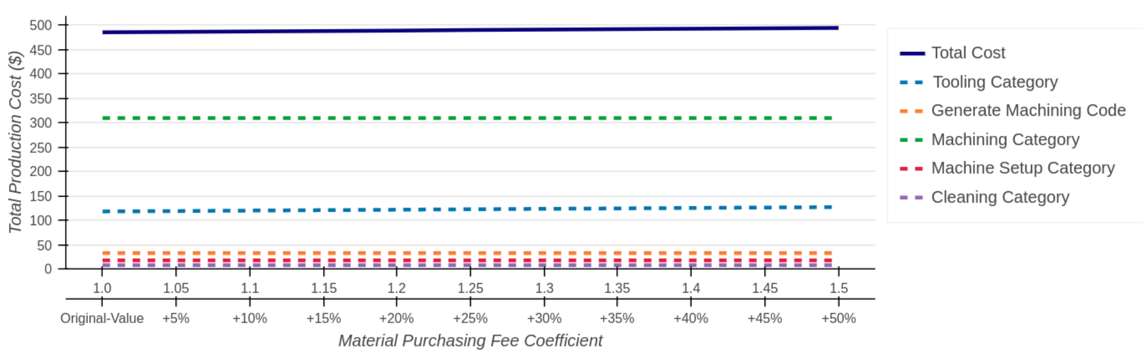

Figure 5.4: The impact of material cost coefficient on production cost (standard design; batch size = 1)

Figure 5.5 shows that the cost of *tooling* and *machining* categories increase as we augment the equipment usage cost. We have also a slight increase in the *cleaning* cost. This is expected from the cost distribution we see in figure 5.1: chart D and the linearity of the relationship between *equipment usage cost* and *production cost* for a given design and batch size (see equations (1) and (3) in section 3.2).

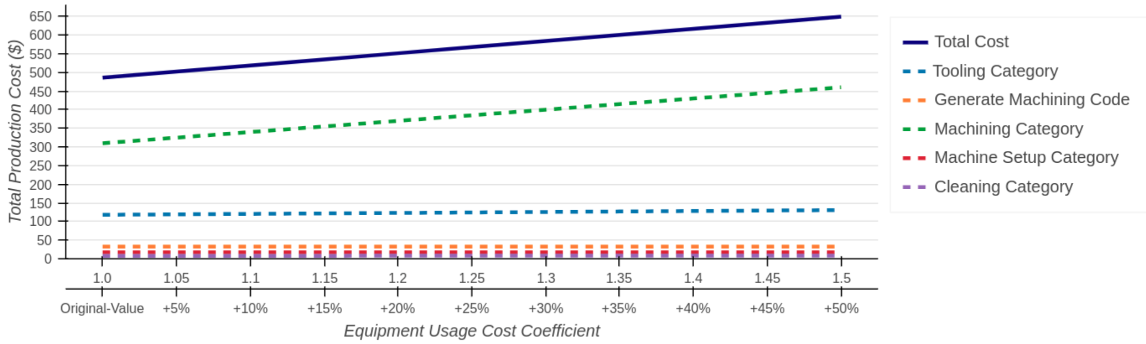

Figure 5.5: The impact of equipment cost coefficient on production cost (standard design; batch size = 1)

After analyzing the impact of each individual resource cost, we compare their effect on the total production cost in figure 5.6. As shown in the figure, the *total production cost* is considerably increased when we augment the *equipment usage cost*, it (*total production cost*) gets little effect when we augment the *labor pay rate*, and it gets very limited effect with the increase of *material purchasing fee*. This result can be justified with the linear relationship between the *resource cost coefficients* and *total production cost* as well as the higher involvement of equipment as compared with labor and material in the SACE process (see figure 5.2: chart A).

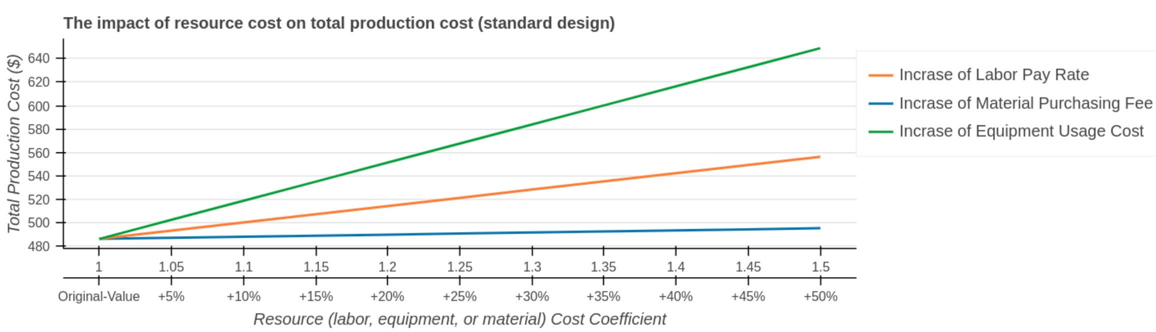

Figure 5.6: The impact of resource cost coefficient on total production cost (standard design; batch size = 1)

We next analyze the sensitivity of the production cost to the changes in the design and batch size. Figure 5.7 shows the effect of design complexity on the cost of different task categories. While *cleaning* and *machining set-up* are not sensitive to the design complexity, the cost of *tooling*, *generate machining code*, and *machining* categories increase for higher design complexities. This was expected from SACE process. The *tooling* category requires more resource for specifying the required in the context of more complex designs. The engineer needs more time to *generate machining code* for complex designs as well. This is because the engineers involved in the tasks need to pay more attention to the design details and convert CAD to CAM appropriately. For instance, fabricating design (B) (*complex*) requires several tool-electrodes. The engineer has to spend more time to include the settings related to the fabrication using multi tools (e.g. which trajectory is machined with which tool-electrode). Further, SACE equipment requires more time for fabricating more complex designs which makes the *machining* category more costly. We use an automatic multi-tool head for machining more complex designs. The extra equipment time for complex designs is related to the higher machining time (e.g. several micro-channels to fabricate one after another), the time that SACE equipment stops, waiting for the head to change the tool-electrode, as well as the need for extra operator inspection while SACE is operating.

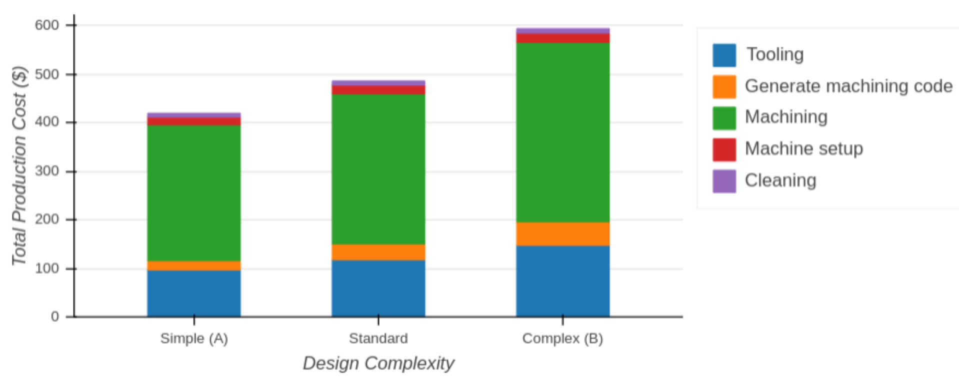

Figure 5.7: The Effect of Design Complexity on Total Production Cost (batch size = 1)

Figure 5.8 shows the effect of batch size on the total production cost. This effect is associated with the *batch size effect* which we discussed in the equations (2), (3), and (4), in section 3.2. We can see in figure 5.8 that the total production cost decreases slowly, with a small slope, as the batch size is increased. This is expected since the *machining cost* is not decreased for higher batch sizes while, as mentioned earlier, *machining cost* constitutes the largest portion of the total production cost (see 5.1: chart A). The cost reduction comes mostly from *tooling* and *generate machining code* categories. Similarly, when we get to higher batch sizes (e.g. from batch size = 100 to batch size = 1000), we can see that the total production cost is not affected much. This is because at some point at larger batch sizes, the cost of *tooling* and *generate machining code* tasks are almost broken down to their highest possible extent, depending on the tasks capacities (see table 4.1), while *machining*, which causes the highest cost among others, does not break down at all when the batch size is increased. This result was expected for SACE process; we justify it in more detail as follows.

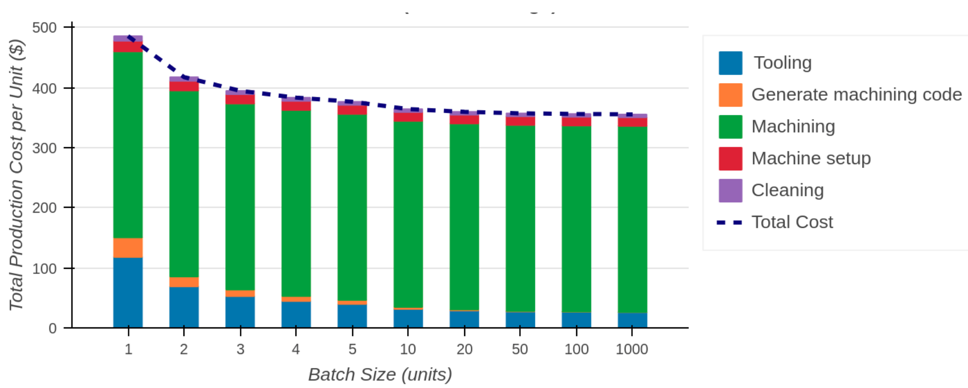

Figure 5.8: The effect of batch size on total production cost per unit (standard design)

The tool and material which is provided in the *tooling* category for the personalized order can be re-used (with a limited capacity) for higher batch sizes. For instance, specified tool-electrodes can be used as is for the same design until they reach their capacity and get replaced. In fact, we can see in table 4.1 that most of the tasks of this category have a variable cost ($fv_{t,i}$=1) and a capacity ($a_{t,i}$) > 1. This breaks down the associated cost to some extent. On the contrary, the task of the *generate machining code* category is a one-time task which is performed for each personalized design. It only has a fixed cost (see table 4.1). Therefore, the cost per unit of this category breaks down and decreases with higher batch sizes. Moreover, increasing the batch size has almost no effect on the *machine setup* category. The *load machining code* task is the only task with a fixed cost within this category and its cost breaks down for larger batch sizes. However, this task is very inexpensive and has limited effect on the cost of the category. The remaining tasks of this category must be repeated for each personalized order (capacity = 1), they are not sensitive to the batch size. Therefore, *machine setup* does not get much effect from batch size. The *cleaning* category gets affected by the batch size at "*clean the fabricated workpeice*" task. As expected, its effect is limited on the production cost since the *cleaning* category makes a very small portion of the total cost (see figure 5.1: chart A). Finally, the tasks of the *machining* category must be repeated (capacity = 1) each time as shown in table 4.1. We have considered that SACE has a single machining-head and machines one product at a time. Besides, SACE is an advanced manufacturing process which fabricates from a CAD file and the fabrication cost will not be broken down when the batch size is increased.

The results discussed above were generated automatically as *WebPMCS Reports*. We showed that WebPMCS works correctly for the SACE process. Next section investigates finding the most cost-effective fabrication route for a given personalized order.

5.2 Finding the Most Cost-Effective Fabrication Route

This section provides the selected task-choices for the nine SACE personalized orders described in figure 4.15. As shown in table 4.1, we have considered alternatives (more than one choice) for three tasks. Figure 5.9 shows the selected task-choices. These choices, in fact, form the most cost-effective fabrication route for each personalized order.

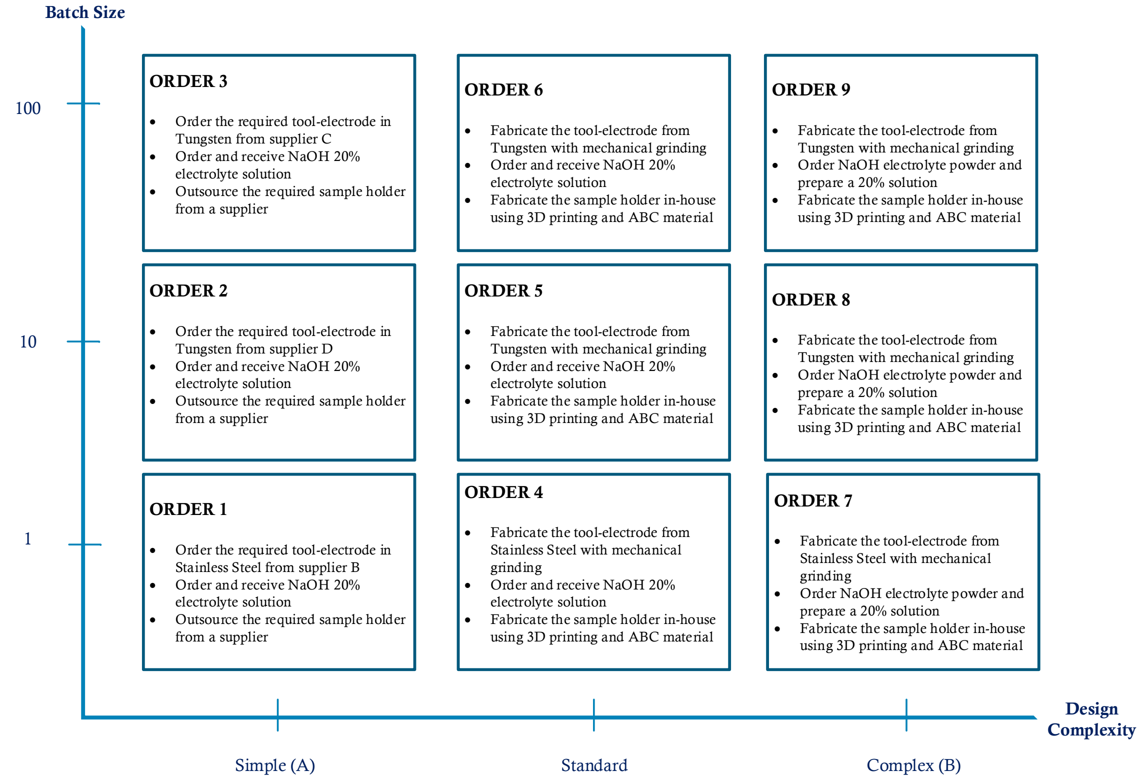

Figure 5.9: Selected task-choices for each personalized order, forming the most cost-effective fabrication route

As seen in figure 5.9, the tool-electrode is outsourced for orders with a *simple* design (orders 1, 2, and 3) while it is fabricated in-house for other orders. As mentioned in section 4.3, the simple design needs only one tool-electrode, the standard design needs two tool-electrodes, and the complex design needs three. Purchasing multiple tool-electrodes is usually more expensive than fabricating them. The reason is that the suppliers usually do not offer any economy of scale for the tool-electrodes. However, we can fabricate several SACE tool-electrodes using a grinder in-house and there are common setup steps for the grinder which breaks down the fabrication cost. This was the case for our study and we entered the relevant parameters in WebPMCS accordingly (see table 4.1). As a result, WebPMCS has decided to order the tool-electrode when only one is needed in order to benefit from the better outsourcing price while fabricating multiple tool-electrodes in-house to break down the fabrication cost and beat the suppliers' price.

Moreover, Stainless Steel tool-electrode is selected for *batch size = 1* (orders 1, 4, and 7) while Tungsten tool-electrode is selected for larger batch sizes. Stainless Steel tool-electrode is less expensive than the Tungsten tool-electrode; however, Tungsten tool-electrodes are more durable and can be replaced later (be re-used more) as compared with Stainless Steel tool-electrodes. We can see that WebPMCS has selected Stainless Steel for lower batch sizes in order to benefit from a better price while selecting Tungsten for higher batch sizes to provide more replacement possibility and break down the cost further. Further, the quality of the purchased tool-electrode could differ for different suppliers, resulting in various task capacities (i.e. the number of times the tools can be re-used). That is the reason why order 2 and order 3 purchase a Tungsten tool-electrode from *supplier D* and *supplier C*, respectively (orders 2 and 3 have the same design but different batch sizes).

As shown in table 4.1, we considered NaOH and KOH as electrolyte options for SACE fabrication. WebPMCS has selected NaOH electrolyte for all the orders. The electrolyte is prepared in-house from electrolyte powder for *complex* designs while it is ordered in form of a pre-made solution for other orders. These results are associated with the suppliers' prices (e.g. the price offered by the supplier for NaOH is less than the price for KOH) as well as our consideration that more complex designs need more electrolyte (see table 4.1). When a more complex design needs more electrolyte, we can either purchase more *electrolyte solution* or purchase more *electrolyte powder* and have the operator spend more time for preparing it. Considering the time it takes from the operator to prepare more electrolyte and the different prices of electrolyte pre-made solution and electrolyte powder, WebPMCS has selected to order NaOH electrolyte powder and prepare in-house for orders 7, 8, and 9.

The sample holder is outsourced for orders with a *simple* design (orders 1, 2, and 3) and is fabricated in-house for other orders. Since fabricating a *complex* design takes more time and potentially produces more vibrations (than a *simple* design), we considered that more complex designs require denser and more solid sample holders in order to hold the workpiece tightly and prevent vibrations from disrupting the fabrication. This means more material usage for fabricating the sample holder in-house or higher prices when it is outsourced to a manufacturing service company. Consequently, WebPMCS found outsourcing the sample holder for *simple* designs and in-sourcing the sample holder for *standard* and *complex* designs more cost-effective.

So far we have validated WebPMCS for SACE, provided some insight for SACE production cost, and selected the most-cost effective fabrication routes for nine personalized orders. Although we used an automatic tool changer (see figure 4.14) and reduced the machining time, it was shown that still *machining* category forms a large portion of production cost in the SACE process. The equipment is the main cost driver in this category (see figure 5.2: chart D). Using the insights we obtained from WebPMCS report, in the next section we evaluate the strategy of using multiple machining heads and tool-electrode heads for the SACE process. This approach could reduce the *machining* cost and make the final product more affordable.

5.3 Multiple SACE Machining/Tool-Electrode Heads

In chapter 4, we discussed SACE machining and illustrated *machining head* and *tool-electrode head* in figure 4.14. We considered a single-head (both *machining head* and *tool-electrode head*) SACE equipment at that point. In this section, we consider having multiple heads for the SACE process as a try to reduce the production cost for mass personalization.

As mentioned earlier, the *machining head* includes the main motor and each *machining head* can have one to several *tool-electrode heads*. Figure 5.10 illustrates this when we have N $(n = 1 \ldots N)$ machining heads, each including M $(m = 1 \ldots M)$ tool-electrode heads. In this document, we call such machine a *n-head equipment with m tool-electrode heads*. The values of n and m will be considered as 1 if they are not specified otherwise. For instance, in our definition, a *three-head machine* will have *three* machining heads ($n=3$), each including *one* tool-electrode head ($m=1$).

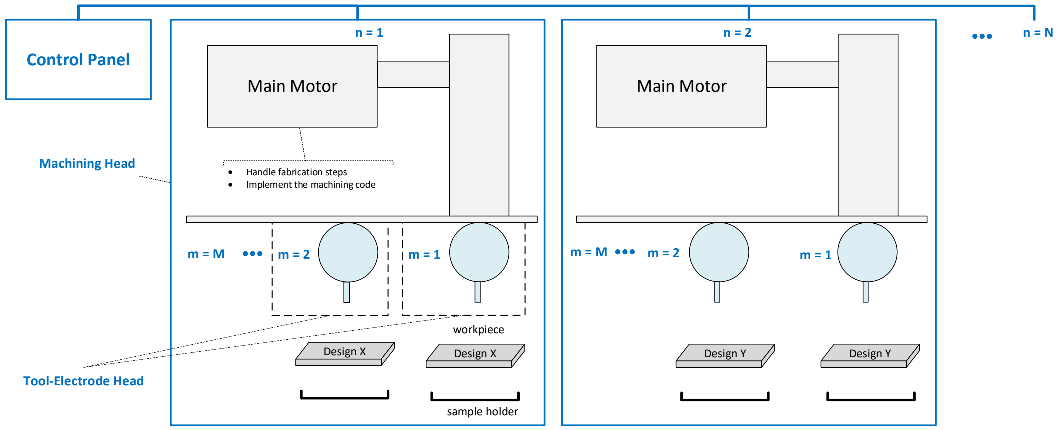

Figure 5.10: Multi-head machining in SACE

Each machining head is independent and will have its own machining code. Therefore, we consider to use different machining heads for different personalized designs. However, inside each machining head, different tool-electrode heads are not independent from each other since they all use the same machining code and their movements are identical. For this reason, we use multiple tool-electrode heads inside a specific machining head in order to fabricate larger batch sizes of a specific personalized design. We can see this in figure 5.10 as well. For n=1 (first machining head), all the corresponding tool-electrode heads fabricate *Design X*. However, we are fabricating *Design Y* for n=2. The price of an extra *machining heads* is usually higher than an extra *tool-electrode head*. Therefore, we do not use a new *machining head* unless it is necessary. In other words, higher batch sizes could be handled using *tool-electrode heads* since they are a batch of a specific personalized design and one *machining head* could process them all at the same time.

In order to evaluate the multiple head approach using WebPMCS, we fixed our fabrication route and, among available alternatives (see table 4.1), considered to "fabricate the tool-electrode from Stainless Steel with mechanical grinding", "order and receive NaOH 20% electrolyte solution", and "fabricate the sample holder in-house using 3D printing and ABC material". We have considered this route for the following sections which evaluate the use of multiple *machining heads* and/or *tool-electrode heads*.

5.3.1 Multiple SACE machining heads

As mentioned earlier, machining heads are independent in SACE process. In fact, a SACE machine with n machining heads is quite similar to n single-head machines arranged beside each other. However, such multi-head machines are usually less expensive than multiple single-head machines. This could reduce the usage cost of each machining head. For an equipment with n machining heads, we consider that each machining head adds $(100\,p)\%$ to the equipment price. Then, the usage cost of the n-head equipment is divided by n in order to obtain the usage cost per hour of each machining head ($ec_{t,i,n}$) (more precisely, $ec_{t,i,n} = ec_{t,i}\,[1 + p\,(n-1)]/n$). The value of p will be between 0 and 1; zero when adding machining heads has no extra cost and 1 for the case where adding a machining head has the same cost as purchasing a new single-head equipment. For instance, if p=*0.8* (about 80% more equipment cost for each added machining head), the usage cost of each machining head of a three-head (n=3) machine will be $ec_{t,i,3} = ec_{t,i}\,[1{+}(3{-}1)\,0.8]/3 = 0.87\,ec_{t,i}$. In this case (three-head equipment), the machining head usage cost is facing a 13% (1-0.87=0.13) decrease compared to a single-head machine. We consider p in our sensitivity analysis in order to obtain insight on the potential benefits of multiple machining heads when the equipment is priced differently.

As an example for illustrating the use of multiple machining heads, figure 5.11 shows a three-head SACE machine. Since each machining head is independent, with separate machining code, we consider to place each designs on a different machining head. In this example, these three are the simple, standard, and complex designs considered earlier (see figures 4.12 and 4.13). As seen in the figure, the automatic tool changer is adjusted based on the design at hand.

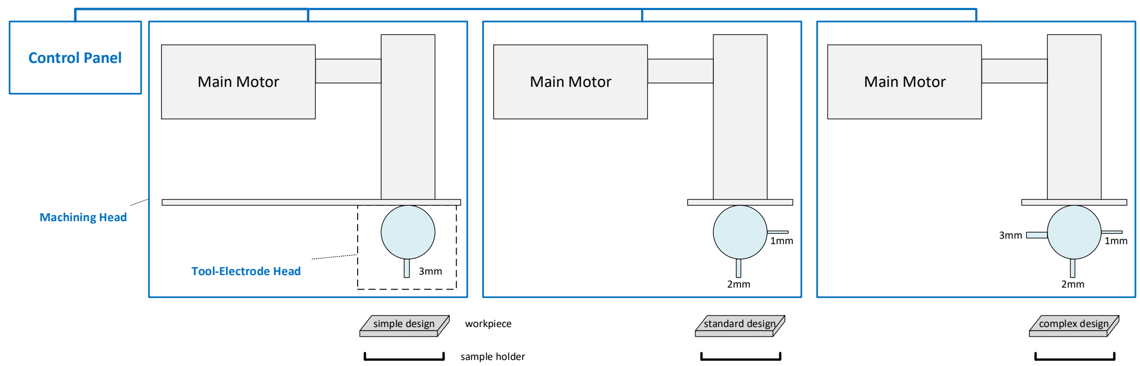

Figure 5.11: Machining Three Designs with Multiple Heads

Figure 5.12 shows the effect of using multiple machining heads on the total production cost for different head prices (p). In addition, for p=0, the cost breakdown is shown in form of a stacked bar chart. In this experiment, for simplicity, we fixed the batch size to 1 and considered that all the designs at hand are *standard*. We assumed that they are unique designs and need to be fabricated using different machining heads, while their parameters (see table 4.1) are identical because of their close features (i.e. we assumed that these unique *standard* designs are similar in terms of *dimension variety* and *machining mode*; see figure 4.13).

We assumed that there is enough demand in the market for different personalized orders and all the machining heads are engaged in the production. In other words, in figure 5.12, for a ten-head machine (n=10) we have considered a batch of 10 (batch size = 10) while for a two-head machine (n=2), batch size = 2 is considered. As we can see in the figure, the *machining* cost decreases as the number of SACE machining heads is augmented. This is because of the lower usage cost of machining heads for multi-head machines. We can also see that, as expected, the slopes of lines are increased as the value of p becomes smaller. This means that, as expected, multi-head machining has more considerable benefits when we have lower machining head prices. The corresponding line for p=1 has a slope of zero since, with current assumptions, we would get no benefit from multi-head machining if the price of adding a machining head is the same as purchasing a new single-head machine.

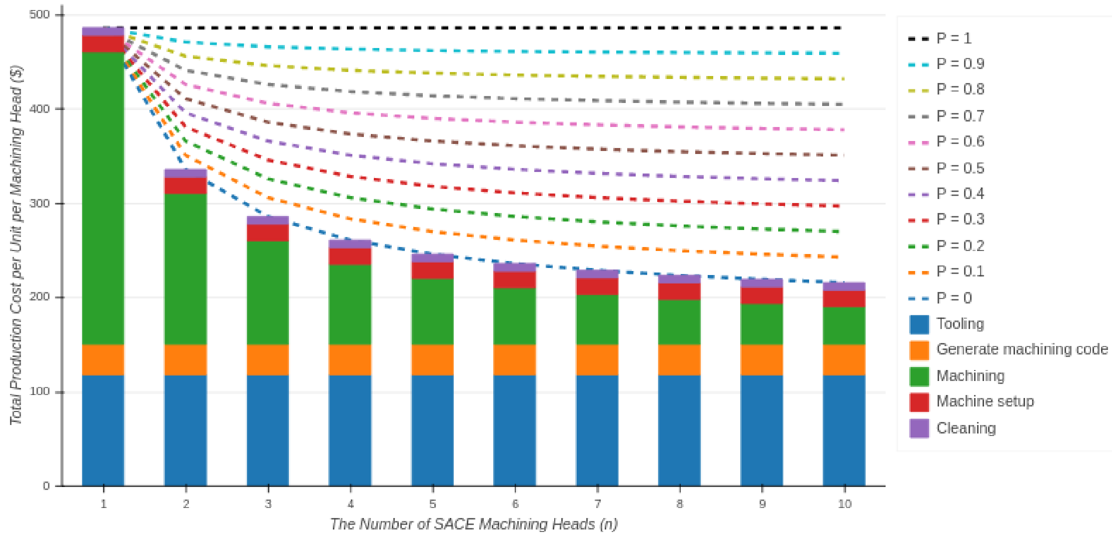

Figure 5.12: The effect of multiple machining heads on production cost

As stated earlier, each *machining head* is independent in fabrication. That is the reason why we can process a different *design* on each *machining head*. Figure 5.12 showed that *p=0* brings the highest reduction in production cost. However, *p=0* is not realistic for multiple *machining heads* since each machining head is similar to a single-head machine and could be expensive. This brings us to the idea of having multiple heads which are not necessarily independent so that we can have a lower *head price* and fabricate higher batch sizes of a specific design in a more cost-effective way. In the next section, we consider having a single machining head (n=1) and will focus on multiple tool-electrode heads (m>1) and how they can benefit the production.

5.4 Multiple SACE Tool-Electrode Heads

As mentioned earlier, the cost of *machining* category is the highest in SACE personalized fabrication. In the previous section, we showed how using multiple machining heads could be useful to reduce the production cost of batch-of-one (batch size = 1) fabrication of different designs. In this section, we consider having a SACE equipment with a single machining head and multiple tool-electrode heads as a potential solution for reducing unit machining cost for larger batch sizes.

On the one hand, as the designs of a batch larger than 1 are all identical (i.e. batch size = the number of final products with the same personalized design), they all could be machined using a single machining head. In fact, we consider that the machining head performs all the necessary motions and fabrication tasks according to the machining code, while multiple tool-electrode heads are controlled by the main motor and follow the exact same movements and procedures (see figure 5.10). Therefore, having multiple tool-electrode heads will be usually much cheaper than having multiple single-head machines. As a result, we could process products in parallel and pay less for the machining. More precisely, we mentioned in section 3.2 that the capacity of a task-choice ($a_{t,i}$) is defined considering tool and equipment capacity (the number of products that the equipment can process in parallel). A machine with multiple tool-electrode heads can process several products simultaneously and, therefore, can increase the capacity of related task-choices. This can reduce the production cost (see equations (1), (2), (3), and (4) in section 3.2). On the other hand, machines with multiple tool-electrode heads might need more resources for setup. In fact, some of the SACE tasks mentioned in table 4.1 must be repeated if we choose to use multi-head machines. This causes extra costs. If we have m tool-electrode heads, the *fabricated/order the tool-electrode* and *fabricate/order the sample holder* tasks must be repeated m times. This is because each SACE tool-electrode head must have separate tool-electrode(s) and sample holder in order to process products in parallel. In other words, by adding extra *tool-electrode heads* we are increasing the capacity of our tooling (sample holder and tool-electrode) which in return causes extra costs. Besides, each *sample holder* and *tool-electrode* could also be re-used several times (see table 4.1 for their capacity); therefore, their cost become more important for large batch sizes. Since tooling cost is quite low in the SACE process, it is possible that the benefits of multi tool-electrode heads outweigh their costs. In this section, we consider this trade-off and analyze this strategy for SACE personalization.

In our consideration, the equipment usage cost per hour of a single-head (n=1) equipment with m tool-electrode heads ($ec_{t,i,1,m}$) will be about $(100\,q)\%$ more for each added tool-electrode head (more precisely, $ec_{t,i,1,m} = ec_{t,i} \times [1 + (m-1) \times q]$). The value of q will be between 0 and 1; zero when adding a tool-electrode head has no extra cost and 1 for the case where adding a tool-electrode head has the same cost as purchasing a new equipment. Although the q=1 could be an unrealistic case, we took it into account for corresponding validations. For instance, if *q=0.1* (about 10% more usage cost for each added tool-electrode head), the price of a single-head (n=1) machine with four tool-electrode heads (m=4) will be $ec_{t,i,1,4} = ec_{t,i} \times [1 + (4 - 1) \times 0.1] = 1.3\, ec_{t,i}$. We consider q in our sensitivity analysis in order to obtain insight on the potential benefits of machining with multiple tool-electrode heads when they are priced differently.

In this section, we consider that the production system has one personalized order at a time and they all have a *standard* design. Figure 5.13 shows the total production cost of a standard design with batch sizes equal to 10, 30, and 100, when q = 1. As we can see in charts A, B, and C, the *tooling* cost increases as the tool-electrode head number is augmented. This is because of the tasks we repeated in order to provide *tool-electrode* and *sample holder* for each tool-electrode head. The total *machining* cost also changes with head number. The trend of the *machining* cost (and hence the total production cost) is not linear since multiple tool-electrode heads increase the machining capacity ($a_{t,i}$) (e.g. a machine with two tool-electrode heads can process two products at the same time) and we later *round the* $bs/a_{t,i}$ *up* (causing non-linearity) for estimating the batch size effect (see equations (1), (2), (3), and (4) in section 3.2). For instance, if we have 4 tool-electrode heads, the capacity of the machining task will be 4. This means that with batch size = 10, we need to use this equipment, which has four tool-electrode heads, three times to fulfill the order ($[1 + \cancelto{1}{fv_{t,i}}(\cancelto{\lceil 10/4=2.5\rceil=3}{\lceil bs/a_{t,i}\rceil} - 1)] = 3$; see equation (3) in section 3.2). In other words, we engage 4, 4, and 2 tool-electrode heads in order to process 10 products. However, if we add another tool-electrode head to have five tool-electrode heads, we can complete the fabrication by using the equipment only two times (i.e. engaging the 5 tool-electrode heads two times). Consequently for fabricating 10 products, as seen in chart A, using a machine with five tool-electrode heads (with rather higher usage cost) twice becomes more cost-effective as compared with using a machine with four tool-electrode heads (with rather lower usage cost) three times. In simpler terms, since we are paying for the machine with multiple tool-electrode head per hour, every tool-electrode head that is not used is a loss. Using a machine with four tool-electrode head for fabricating 10 products leaves 2 tool-electrode heads vacant at its third use, which at the end makes us select a machine with four tool-electrode heads instead. With the same reasoning, we can understand why the *total cost* lines of charts A, B, and C are not linear. What is more, since we have considered q = 1, adding each tool-electrode head causes the cost of a new equipment in addition to some extra setup cost. Therefore, as expected, when q = 1, using multiple tool-electrode heads provides no financial benefit, in the considered context. As seen in the figure 5.13, the optimal number of tool-electrode heads are n=1 for Chart A, n=1 or n=3 (multiple optimal value; same production cost) for Chart B, and n=1,2,5, or 10 for Chart C. While having n=1 as an optimal number for too-electrode-head is an obvious answer (since multiple tool-electrodes do not reduce the production cost when q=1), other optimal answers are obtained by WebPMCS in such a way that the total production cost is minimized considering the *machining* and *tooling* cost trade-off.

After considering $q = 1$ in figure 5.13, we considered other values for q and ran the experiment. Figure 5.14 shows the result for $q = 0$. Although when $q = 0$, adding tool-electrode heads causes no extra equipment usage cost, we would need to pay extra setup costs in order to fabricate using multiple tool-electrode heads. We can see in charts A, B, and C that as we increase m (the tool-electrode head number), the *machining* cost is reduced but the *tooling* cost is increased. Considering this trade-off, $m = 10$, $m = 15$, and $m = 25$ are selected as the optimal equipment tool-electrode head numbers for SACE glass micro-machining in charts A, B, and C, respectively. Figure 5.15 shows the related result when $q = 0.5$. We can see in the figure that m=5, m=10 and m=20 are selected as the optimal tool-electrode head number for charts A, B, and C, respectively. With $q = 0.5$, using machines with multiple tool-electrode heads has a trade-off between *higher usage cost and setup cost* at one side and *more task capacity* at the other side.

Figures 5.13, 5.14, and 5.15 showed that using multiple tool-electrode heads could provide considerable financial profit to personalized fabrication. We can also see that the optimal tool-electrode head number could change depending on the batch size (*bs*) of the

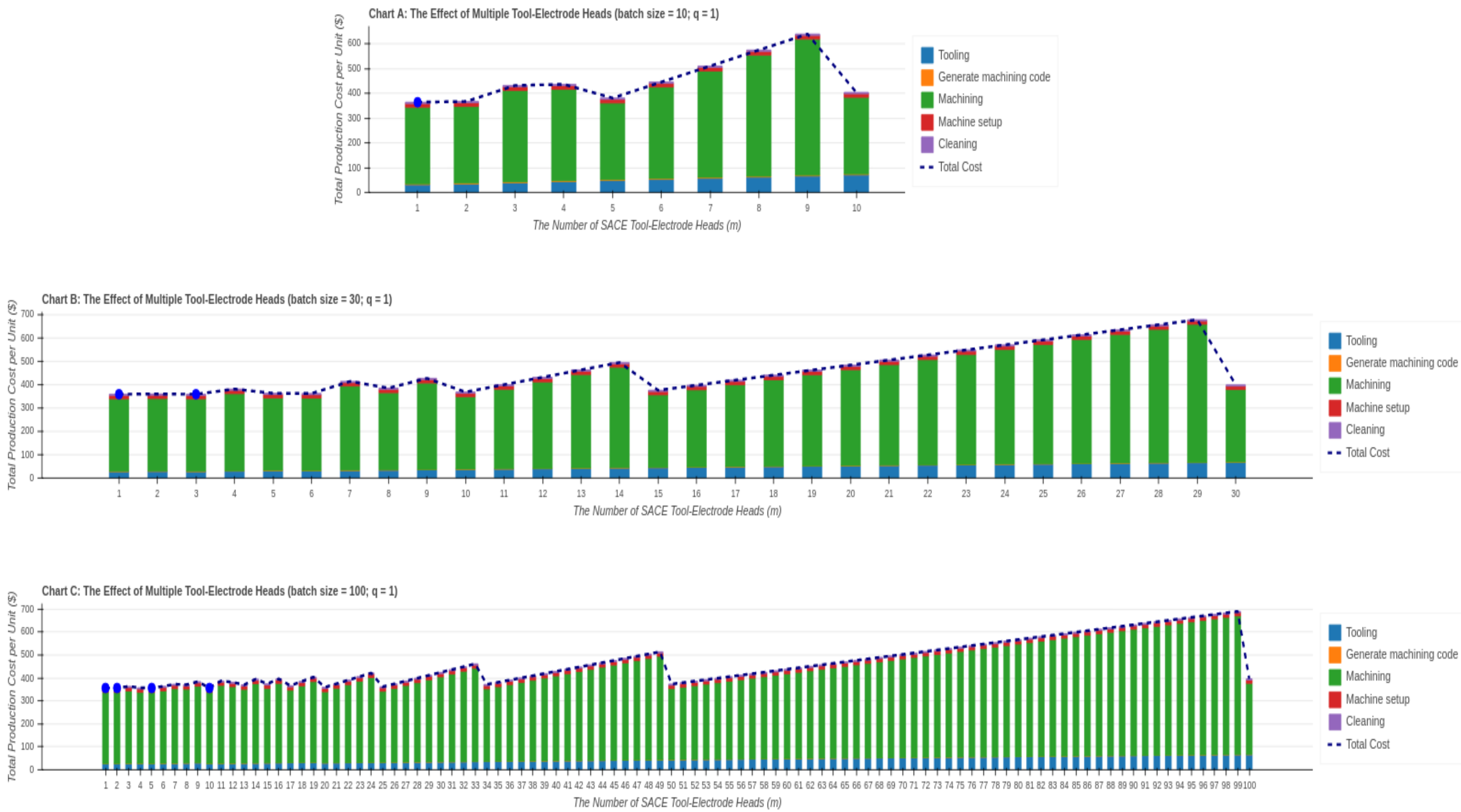

Figure 5.13: The effect of using multiple tool-electrode heads on total production cost of a single-head (n=1) machine (q = 1)

Figure 5.14: The effect of using multiple tool-electrode heads on total production cost of a single-head (n=1) machine (q = 0)

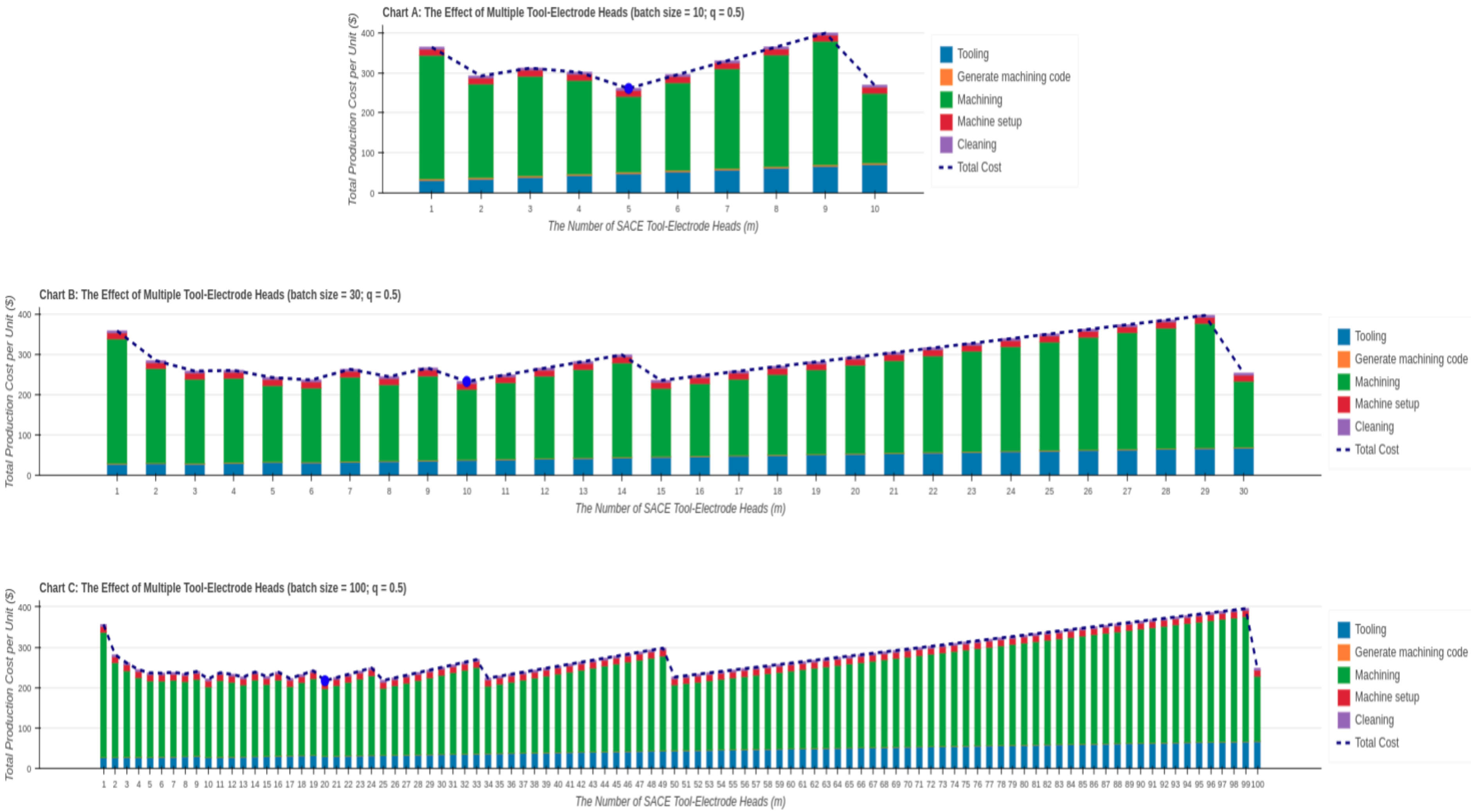

Figure 5.15: The effect of using multiple tool-electrode heads on total production cost of a single-head (n=1) machine (q = 0.5)

personalized order at hand as well as the price of added tool-electrode heads (q). Figure 5.16 shows the result of the experiment performed by WebPMCS in order to obtain the optimal tool-electrode head for different values of bs and q. For instance, if a company using the SACE process only receives *standard designs* (as considered at the beginning of this section) with *batch size = 30*, and *q = 0.1* (i.e. each added tool-electrode head adds about 10% to the price of the equipment with a single tool-electrode head), purchasing a machine with 10 tool-electrode heads would be optimal for the company ($m^* = 10$). We can see in the figure that, as expected, the optimal number of tool-electrode head is reduced as the tool-electrode head price is increased. The results shown in figure 5.16 for *q=1*, *q=0*, and *q=0.5* confirm what we obtained from WebPMCS report in figures 5.13, 5.14, and 5.15, respectively.

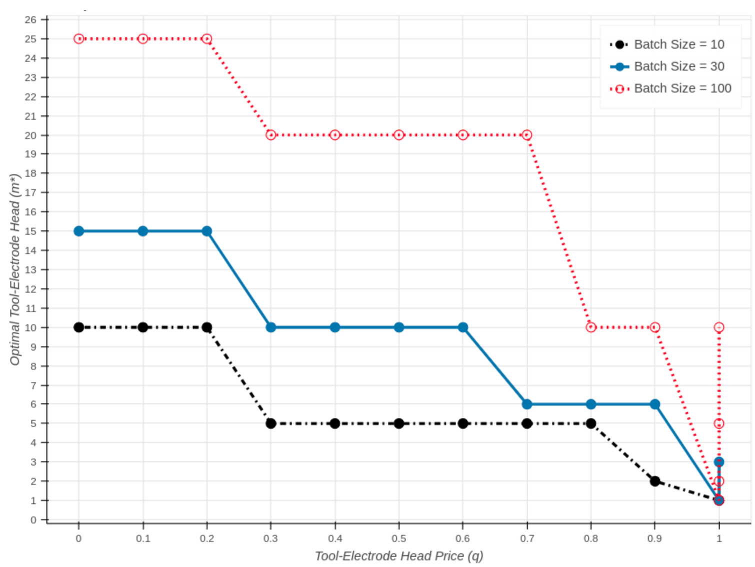

Figure 5.16: The optimal number of tool-electrode heads for a single-head (n=1) machine for different tool-electrode head prices and batch sizes

As mentioned earlier, this section has the assumption of having one personalized order at a time in the production system. Therefore, the optimal tool-electrode number shown in figure 5.16 represents the scenario when customer-specific orders enter the production system one by one and the manufacturing company has no information about the distribution of personalized orders. If we have access to machines with different numbers of machining head, this approach could work well. We can receive a personalized order and select the optimal tool-electrode head from figure 5.16 based on bs and q.

So far we have discussed multiple *machining heads* for batch-of-one fabrication of several unique designs as well as multiple *tool-electrode heads* for different batch sizes of a specific personalized design. There are, however, other scenarios where the manufacturing company needs to purchase a multi-head equipment with the optimal number of *machining heads* and *tool-electrode heads* for mass personalization. In the following section, we investigate multi-head fabrication when a set of SACE personalized orders are at hand.

5.4.1 Multi-Head Fabrication of a Set of Personalized Orders

In this section, we assume that we have several SACE orders with different designs, batch sizes, and demands as shown in table 5.1. The *demand* column in the table represents the number of personalized orders with similar (but not identical) features. In fact, we assumed that, for instance, row 1 of the table represents having 100 personalized orders, each having batch size = 10 and a unique design with identical features of design B (see figures 4.12 and 4.13) which is a *complex* design. In other words, for simplicity, we have considered in this section that we can have unique *complex* designs in our production system which have the same set of parameters as design B (see table 4.1). Similarly, we have different orders with *standard* and *simple* designs as shown in table 5.1. The demand considered for different orders are random numbers by considering an increasing market trend towards *complex* and *low-batch* fabrication. That is the reason why row 1 with *batch size = 10 (lowest)* and *design = complex (highest level of complexity)* has the largest demand.

Table 5.1: Personalized orders of the production system for multi-head fabrication

Order #	**Batch Size**	**Design**	**Demand**
1	10	complex	100
2	10	standard	80
3	10	simple	60
4	30	complex	80
5	30	standard	60
6	30	simple	40
7	100	complex	60
8	100	standard	40
9	100	simple	20

Considering that a *machining head* includes the main motor and is usually more expensive as compared with the *tool-electrode head*, we assumed the values of p*=0.6* and q*=0.1* respectively. We earlier discussed the effect of multiple *machining heads* and *tool-electrode heads* on the equipment usage cost in sections 5.3.1 and 5.4. Here we can have a n-head machine with m tool-electrode heads and consider the corresponding effects on equipment usage cost and task capacities (e.g. for the equipment usage cost, $ec_{t,i,n,m} = ec_{t,i}\,[(1 + p\,(n-1))/n][1 + q\,(m-1)]$). WebPMCS obtained n*=3* and m*=10* as the optimal values of n and m for the production system at hand. The machining heads handle the different designs in our production system and the tool-electrode heads manage different batch sizes in the most cost-effective way. Figure 5.17 illustrates the state of optimal multi-head fabrication for this production system.

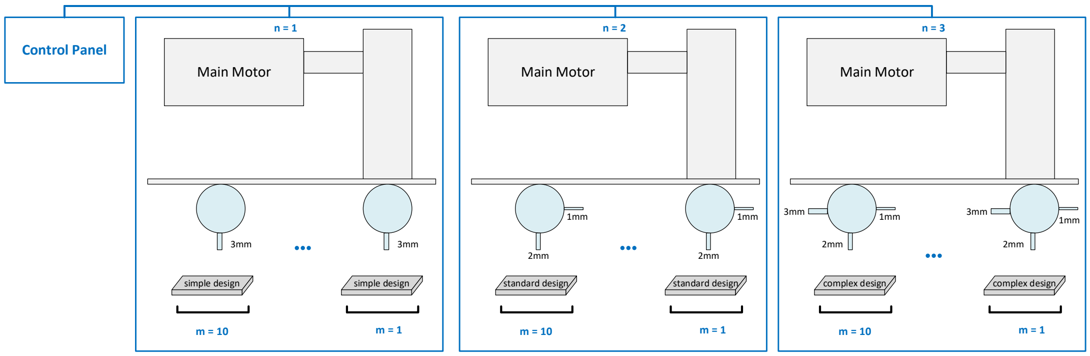

Figure 5.17: The optimal multi-head fabrication for a defined set of personalized orders

5.5 Managerial Insights

In section 5.1, we showed that labor pay rate does not have considerable effects on SACE production cost. For a SACE manufacturing company in a developed country like Canada, this low sensitivity to labor salary can potentially make operating at home more productive and economically viable as compared with outsourcing to lower-wage countries. This is good news for personalization strategies in developed countries. Implementing personalization could need high-skilled labor in the production line with potentially higher salaries. At the same time, making products at home could facilitate supervision, training, product shipping, and quality control. Therefore, low sensitivity to labor could make outsourcing to other countries less productive and create new job opportunities in developed countries.

Figure 5.6 illustrated that SACE production cost is quite sensitive to equipment cost. Depending on the market situation, it could be a good strategy to purchase the equipment (especially the main equipment of the process) instead of outsourcing it to manufacturing service companies. In case of sudden market changes, owning the equipment could bring more financial stability to the manufacturing company. It also means that we can potentially reduce the cost of final product considerably by improving the equipment efficiency.

Section 5.3 showed that multi-head machining could be beneficial for mass personalization. We evaluated the strategies of having multiple *machining heads* and/or *tool-electrode heads* for SACE personalized fabrication. Both showed to provide financial benefits to the company. The results of sensitivity analysis tests conducted on the price of adding extra machining heads could be used by industrial machine manufacturing companies in order to see whether or not it is cost-effective to produce multi-head machines. They can evaluate the added value they could provide to a manufacturing company with their multi-head equipment. The analysis performed on machines with multiple tool-electrode heads and q, the price of added tool-electrode head, could provide similar insights as well. The result of the analyses can also be used by the manufacturing companies practicing mass personalization in order to decide if purchasing a multi-head machine for their shop floor is worthwhile. They can also decide on the optimal number of *machining head* and *tool-electrode head* using the WebPMCS report.

In section 5.4.1, we provided the optimal multi-head production system for a set of personalized orders at hand. One important point of consideration here is that *machining heads* tend to be useful for *unique designs*, *tool-electrode heads* are useful for handling *large batches* of a specific design, and *automatic tool-changer* can be beneficial for more complex designs. Depending on market needs, appropriate machines could be made by industrial machine fabricators.

Chapter 6

Conclusion and Future Research

Concluding Remarks

The undergoing market trend towards complex personalized products was the main motivation of this research. Enabling Mass Personalization (MP) in manufacturing can contribute to the Industry 4.0 philosophy, the term for the fourth industrial revolution featured with automation and data exchange, and bring many advantages to the customers and companies. At this point, investigating MP in manufacturing industry is paramount. Considering that MP aims at providing individualized products at prices close to mass production, enabling affordable personalization in manufacturing became the first goal of this research. After perusing the literature, we confined our attention to process/resource selection for MP in an on-demand fabrication context. Our contribution was a web-based decision-support tool capable of finding the most cost-effective fabrication route for each customer-specific order. We developed a cost-estimation model for the tool and considered labor, material, and equipment resources as the cost drivers. We took into account the effect of personalized *design* and *batch size* on the estimated cost. At the end, considering SACE process as our case-study, we validated the tool and presented the related results.

Conducting this study had its own challenges and limitations. First, designing and developing WebPMCS was challenging as it needed various web development and data analysis practices in order to develop the GUI, customize the admin panel, read from and write to the database, analyze the data, create corresponding charts automatically, and perform the decision-making process based on the user inputs. Second, we did not have access to the data of different manufacturing technologies. If we had access to the data of glass micro-machining using wet etching, laser machining, and/or mechanical mirco-drilling processes, for instance, WebPMCS would have processed the data automatically and the generated reports could be compared with the SACE results and provide potentially valuable insights. Third, collecting the data from different suppliers for the SACE process was quite time-consuming.

Future Research Directions

To extend this study, we separately suggest possible extensions for the chapters. In chapter 3, the methodology could be extended in several aspects. First, we can add more criteria to the decision-making. In addition to the cost-effectiveness which we considered in our study, the *surface quality* and *lead time* could be investigated as other potential decision-making criteria. For instance, when a customer has specified a delivery time for a personalized order, we might decide to select a less cost-effective task in order to reduce the lead time. Similarly, high surface quality could affect our process/resource selection. Second, with more criteria, more complex algorithms could be used for the multi-criteria decision-making which could result in selecting fabrication routes more effectively. Third, the decision-making process could become more dynamic when extended. In the current study, we select from available task-choices for different individualized orders while the total number of tasks and task-choices are fixed for each personalized order. As an extension, we could add/remove tasks and task-choices based on the personalized order at hand. For example, the design features might limit our task-choices (e.g. we would need to use a certain type of electrolyte) and a *complex* design might need an extra cleaning task. Fourth, in our current model, WebPMCS accepts several user inputs related to the personalized design in order to consider the *design effect* on the tasks. As a future extension, an algorithm could be developed to auto-fill these user inputs based on the CAD file of the customer-specific design. Such algorithm could use machine learning techniques and perform the auto-fill using the history of the *process/resource selection* and *production cost* of different customer-specific orders.

In chapters 4 and 5, a further work could be considering more manufacturing technologies and examining more personalized orders for each. Considering more orders with unique designs and batch sizes would provide the potentials for evaluating more personalization ideas and strategies. Another promising idea would be the *intelligent grouping of personalized orders* to reduce the machining setup cost. If we use this idea in glass micro-machining, personalized orders with different designs could be grouped in a master slide and be fabricated together. At the end, different designs will be cut in their desired shape. After evaluating this idea with more data, an algorithm could be developed to decide if it is more effective to group the personalized orders at hand. The algorithm could take into account the cost of cutting the orders at the end, glass waste, machining set-up, and fabrication time and cost, among other criteria. In addition, *fabricating the orders* and *cutting the orders from the master glass slide into desired shapes* could be done using different manufacturing technologies in order to optimize the production cost. Cutting the borders of personalized orders might require limited fabrication quality, hence faster and less expensive manufacturing processes could be used for that.

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