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Developing a Quick Response Product Configuration System under Industry 4.0 Based on Customer Requirement Modelling and Optimization Method

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Abstract: In the Industry 4.0 environment, the new manufacturing transformation of mass customization for high-complexity and low-volume production is moving forward. Based on cyber-physical system (CPS) and Internet of things (IoT) technology, the flexible transformation of the manufacturing process to suit diverse customer manufacturing requirements is very possible, with the potential to provide digital "make-to-order" (MTO) services with a quick response time. To achieve this potential, a product configuration system, which translates the voice of customers to technical specifications, is needed. The purpose of this study is to propose a methodology for developing a quick-response product configuration system to enhance the communication between the customer and the manufacturer. The aim is to find an approach to receive requests from customers as inputs and generate a product configuration as outputs that maximizes customer satisfaction. In this approach, engineering characteristics (ECs) are defined, and selection pools are initially constructed. Then, quality function deployment (QFD) is modified and integrated with the Kano model to qualitatively and quantitatively analyze the relationship between customer requirements (CRs) and customer satisfaction (CS). Next, a mathematical programming model is applied to maximize the overall customer satisfaction level and recommend an optimal product configuration. Finally, sensitivity analysis is conducted to suggest revisions for customers and determine the final customized product specification. A case study and an OrderAssistant system are implemented to demonstrate the procedure and effectiveness of the proposed quick response product configuration system.

Keywords: industry 4.0; make-to-order strategy; product configuration system; customer requirement modelling; Kano model

1. Introduction

In the third industrial revolution, information technology facilitated human control of the manufacturing process. Since then, the production line gained flexibility to produce parts with minor variation [1]. Now, in the fourth industrial revolution, also known as Industry 4.0 [2], the underlying technologies such as big data analytics, advanced cyber-physical systems (CPS), and Internet of things (IoT), enhance more flexibility by enabling coordination and integration across the entire manufacturing process, transforming traditional factories to smart factories [3–6]. These new digital technologies enable new ways of developing products and production systems and may improve infrastructure for sharing information [7]. The gaps between customized ordering, function and design, and production are being bridged. Hence, Industry 4.0 is characterized by a paradigm shift from high-volume to low-volume production [6,8].

The concept of Industry 4.0 joins technological achievements with a vision of a digital, intelligent, and automated manufacturing environment. It brings the guaranteeing flexibility and high efficiency of production, integration of different activities, and effective communication between a client and producer [9–11]. Today, companies and their production systems face challenging issues including a complexity derived from a high variation of products [8,9]. These high-complexity/low-volume environments driven by Industry 4.0 trend and techniques represent a very difficult and challenging situation for production companies [12–15]. In today's practice, small and medium-sized enterprises (SME) can apply smart factory production line solution embedded with IoT and CPS technology to embrace the opportunity of small lot sizes, different product lines with low budgets for automation investments [8,12,16–18]. By equipping this, the gap experienced in today's manufacturing environment can be filled and a kind of highly flexible, productive, high-complexity/low-volume, and SME-friendly can be a new paradigm [8,13]. Therefore, the management of described technological challenges in a high-complexity and low volume environment can be considered as the core competency for manufacturing industries, especially for SME manufacturers [13,19]. How to acquire high variety of clients' requirements and meet the requirements of digital manufacturing world, smart factory should be a new answer with new concepts of configurable/mass customized order fulfillment process with product configuration systems [9,20].

A smart factory consists of smart machines, warehousing systems, and production facilities. All modules are deeply intertwined, exhibiting multiple and distinct actions, and controls on each other [21]. Smart factories allow individual customer requirements to be met, making profits with unit production. The Industry 4.0-driven smart factory can bring rapid product development and efficient production [9,11]. The new way of production exposes manufacturing companies to a new environment with opportunities and threats [21]. The related works reported in the literature about this mass customization strategy can be classified into three major categories [13,22]. The first one which was initialized by advanced Industry technology such as IoT and CPS is about the automated, robotized production aspect between suppliers and producers for providing required maintenance service with IoT and CPS and cloud computing. This part is a driver and a bridge to drive the transformation and give a linkage of the following second and third classification in the industrial supply chain. The second one is corresponding to the product configuration aspect between customers and producers, such as new digital product design process and order fulfillment process in smart approaches. Processing these configuration data effectively and providing quick reaction to clients' requirements will be the key issue of achieving mass customization strategy in a high-complexity and low volume environment [10,23,24]. There has thus far been relatively little research into the area [14,23]. Studies about acquisition of knowledge, representation of knowledge, analysis of identified knowledge and searching, accessing and sharing knowledge, which are corresponding to order configuration and product design, is at the initial stage of product manufacturing process [9,12]. The research is still at the early stage in developing product configuration system under Industry 4.0, not to mention a paucity of literature on this subject [13,14]. The final aspect is about the enhancement and transformation of advanced manufacturing process. Industry 4.0 based technology drive an enhanced enterprise resource planning system and reconfigurable manufacturing system to effectively deal with high variety of knowledge design specifications from orders to achieve product design, product schedule, production control and to fulfill the whole manufacturing procedures. The majority of research in Industry 4.0 based manufacturing issues has focused on this topic [13,14].

How a company responds in the new environment and how their resources are to be distributed to optimize production and product transactions within their capability are serious issues [19]. It is vital for companies to directly collect dynamic user requirements and make wise decisions in a short period of time. It is expected that a configuration system could benefit companies by transforming customer voice into configurations. However, existing configuration systems are not likely to adapt well to the potential of Industry 4.0 and meet the dynamic customer requirements. Currently, a typical strategy of customization named make-to-order (MTO) is providing selections of subassembly to customers to configure the products themselves and then place their orders [16,25]. MTO is a business production strategy allowing consumers to purchase products that are customized to their specifications. It is also a manufacturing process in which the production of an item begins only after a confirmed customer order is received, otherwise known as mass customization [16,25]. An MTO manufacturer starts to work on an order only after it has been placed by the customer. MTO is characterized by back orders with zero inventories as each customer order is unique and cannot be manufactured in advance. Consequently, the main driver in MTO operations is the new transformation under Industry 4.0 about customer orders [26,27]. In view of the various products and changing demand, companies adopt MTO and quick response manufacturing (QRM) strategies to be able to respond quickly to user demand through the quick design and production of products. Quick response (QR) is a management concept created to increase consumer satisfaction by shortening the lead time from receiving an order to delivering the product, increasing the cash flow. In this process, manufacturers do not actually hear from customers directly but only receive the orders they place [28]. Yet, customers may not know whether their choices will satisfy their needs, and manufacturers may provide insufficient selections without knowing what customers really need [29]. In addition, the focus is largely on developing product configuration models to transform fixed, collected customer requirement data into high volume and specific specifications, which fails to consider the practical condition of dynamic, customized order placement from online customers.

In summary, a limited number of studies leverage dynamic customer requirements for the order fulfillment and product configuration process of high-complexity products under Industry 4.0 [28,30–32]. With this new and effective way of order fulfillment and product configuration for the new manufacturing demand of mass customization for high-complexity and low-volume production, there is a new research gap that needs to be bridged [8,33]. The key to success is quickly and effectively reacting to diverse and dynamic customer requirements, and bringing the customized products to market in a shorter period of time. Hence, the objective of this research is to develop a novel model of order placement with product configuration to dynamically respond to customer order requirements. To meet this aim, several challenges have to be addressed: (1) There is no effective communication channel between manufacturers and customers. Currently, manufacturers only provide fixed assembled parts without direct communication with customers. As a result, a manufacturer may fail to swiftly respond and fulfill customer requirements. The disadvantage may even accumulate in the future. (2) Customers may not express their requirements clearly and thoroughly. (3) There are many constraints, such as budget and manufacturing capacity, in meeting user requirements.

To address the above challenges, the following is considered: (1) Engineering characteristics (ECs) are defined and selection pools are constructed to consider constraints of manufacturing capacity. (2) A mathematical programming model is applied to maximize the overall customer satisfaction level and recommend optimal product configuration. (3) Sensitivity analysis is conducted to provide customers with more selections. These methods are embedded in the proposed novel and adapted configuration system.

The rest of the paper is organized as follows: Section 2 gives an introduction to the related studies. Section 3 introduces the framework of customer requirement modelling with an optimization approach and the key phases to integrate ECs, customer requirements (CRs), and customer satisfaction (CS) into the optimization model. A practical case study is illustrated in Section 4 with the case of laptop customized production. In addition, a new scenario with a product configuration recommendation system design is described. The authors conclude this work with a discussion of the industrial implications and contributions in Section 5.

2. Literature Review

2.1. Product Configuration System

The product configuration system offers tailored products with short lead time to market in a mass customization environment. It bridges the gap between CRs and product ECs as well as assists in order acquisition and fulfillment [28,34]. Generally, it is based on an MTO strategy that configures predefined engineering characteristics upon the placement of orders, to satisfy diverse CRs [35]. The product configuration system utilizes CRs as inputs and derives the optimized recommended ECs as outputs to automatically generate a bill of material (BOM) for manufacturing [30,35,36].

Many pieces of research have been carried out in the field of the product configuration model under Industry 4.0. Schuh et al. [37] refined the product configuration process based on the similarities between product variance to increase transparency in order processing and better control the quotation process. Wei et al. [28] presented a product requirement modelling and optimization method based on product configuration design. The characterization of the properties of products (e.g., parts, components) was utilized to express the product requirements in the requirement modelling process and implemented in the product function and structure model. Zheng et al. [31] proposed a personalized product configuration process to determine design attributes in a cloud-based adaptable product configuration. The adaptable interfaces enable the efficient changing of optional and personalized modules among different service providers with respect to the dynamic changes of CRs. Tang et al. [38] developed a new bi-objective optimization model with the consideration of a customer satisfaction index (CSI) and greenhouse gas (GHG) emission of products in product configuration. Zawadzki and Zywicki [9] proposed a hybrid prototyping digital product configuration model with virtual reality, virtual prototyping, and rapid prototyping to generate design specification of orders to link to the process of control of production flow. Up to this point, however, research about product configuration system facing the challenges of mass customization with high-complexity, low-volume products, and production was still lacking. Related studies about high-complexity, low-volume products, and production are discussed in the next section.

2.2. High-Complexity, Low-Volume Products, and Production

The definition of complexity was defined by Bhise [33]: "The complexity of a product can be attributed to an increase in the number of parts; number of systems needed to accomplish product functions; number of external systems affecting the product; types of technologies associated with the system; number of interfaces among the systems; number of variables associated with the systems and their interfaces; number and types of users and uses and variations in the operating environments and number of disciplines or specialized fields needed to analyze, design, and evaluate various components and systems". A natural consequence of highly complex products is a more complex design process, which needs more design support [8]. Highly complex products are more common in low-volume than high-volume production. That is to say, high-volume production is often linked to simple products, whereas low-volume production is often linked to customized products [8].

Synnes and Welo [8] summarized the characteristics of "High-volume manufacturing of low-complexity products (high volume, low complexity, HVLC)" and "Low-volume and customized manufacturing of high-complexity products (low volume, high complexity, LVHC)" from previous studies. HVLC consists of attributes of "small and simple interchangeable parts", "standardization", "innovation process of product development to customer demand", "focus on manufacturability", "specialized tools and fixed machines", and "economies of scale". LVHC consists of attributes of "large and complex parts", "customization", "innovation process of customer demand to product development", "large machining center, common tools and flexible machines", and "fewer parts to share costs" [39,40].

Under the incremental manufacturing circumstances of Industry 4.0, it is easy to re-construct a flexible production line with a cyber-physical system to collect various information and realize what and how many product specifications could be customized. To augment the potential scenario, the authors consider that a configuration system under Industry 4.0 should meet the following requirements [8,16,26,27]: (1) Directly collecting and meeting customer dynamic requirements. In a typical procedure, a customer discusses and negotiates through a sales interview and places an order with the assistance of sales office personnel. Sales departments consult and obtain technical advice or feedback from technical departments to verify the correctness and compatibility of the recommended configuration. Efficiency would be impaired by a communication barrier and subjective bias. However, the existing configuration system puts more emphasis on transforming customer requirements into manufacturing requirements for conventional high-volume manufacturing for technical personnel, as shown in Figure 1a. Instead of using mass requirements (HVLC) as input, the novel and quick-response product configuration system should be able to handle individual customer requirements (LVHC), as shown in Figure 1b. (2) Good interaction with customers. Customers do not know the details of the product configuration they really need. Hence, the quick-response product configuration system should be able to assist sales personnel in responding to customers to provide appropriate configurations by their particular customer preference. Figure 1 illustrates the roles of the conventional configuration system and the novel configuration system in two different contexts of high-volume manufacturing of low-complexity products (Figure 1a) and low-volume and high-complexity customization manufacturing under Industry 4.0 (Figure 1b). Hence, the authors intend to propose a methodology of designing a novel quick-response product configuration system to enhance the communication between the service demanders (customers) and the manufacturers.

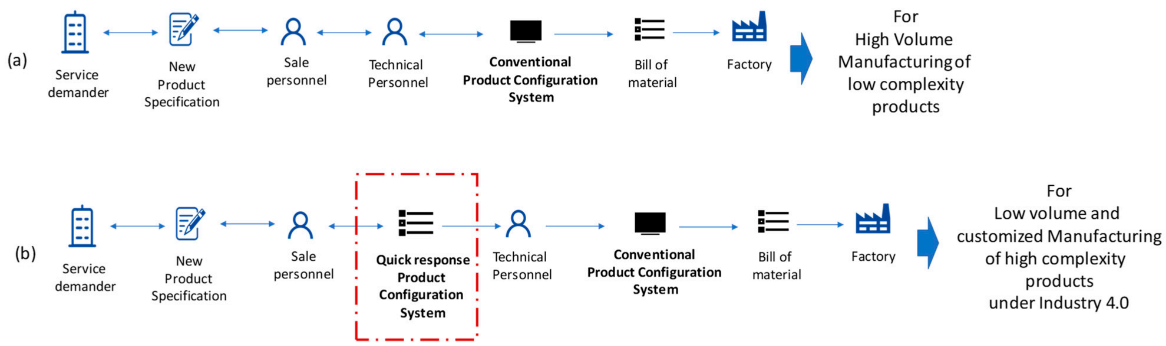

Figure 1. (**a**) Conventional product configuration system; (**b**) required quick-response product configuration system under Industry 4.0.

The increasing demand for customization and short product lifecycles forced the further transformation of the organizational structures of industrial production [41,42]. For the growing complexity of products and process, collaboration becomes more important, especially for small and medium enterprises (SME), which maintain limited resources [1]. CPS and IoT enable coordination through the entire manufacturing process. They enable real-time monitoring, remote control, flexible optimization, and automation [43].

3. The New Approach Framework

This study proposes a novel quick-response product configuration system that could generate an optimal product configuration to maximize customer satisfaction under a budgetary constraint. A new product configuration system was established based on the proposed design model (as shown in Figure 2) that insists of four phases, namely: (1) Engineering characteristics definition; (2) customer requirements modelling; (3) formulation and optimization; (4) review and recommendation.

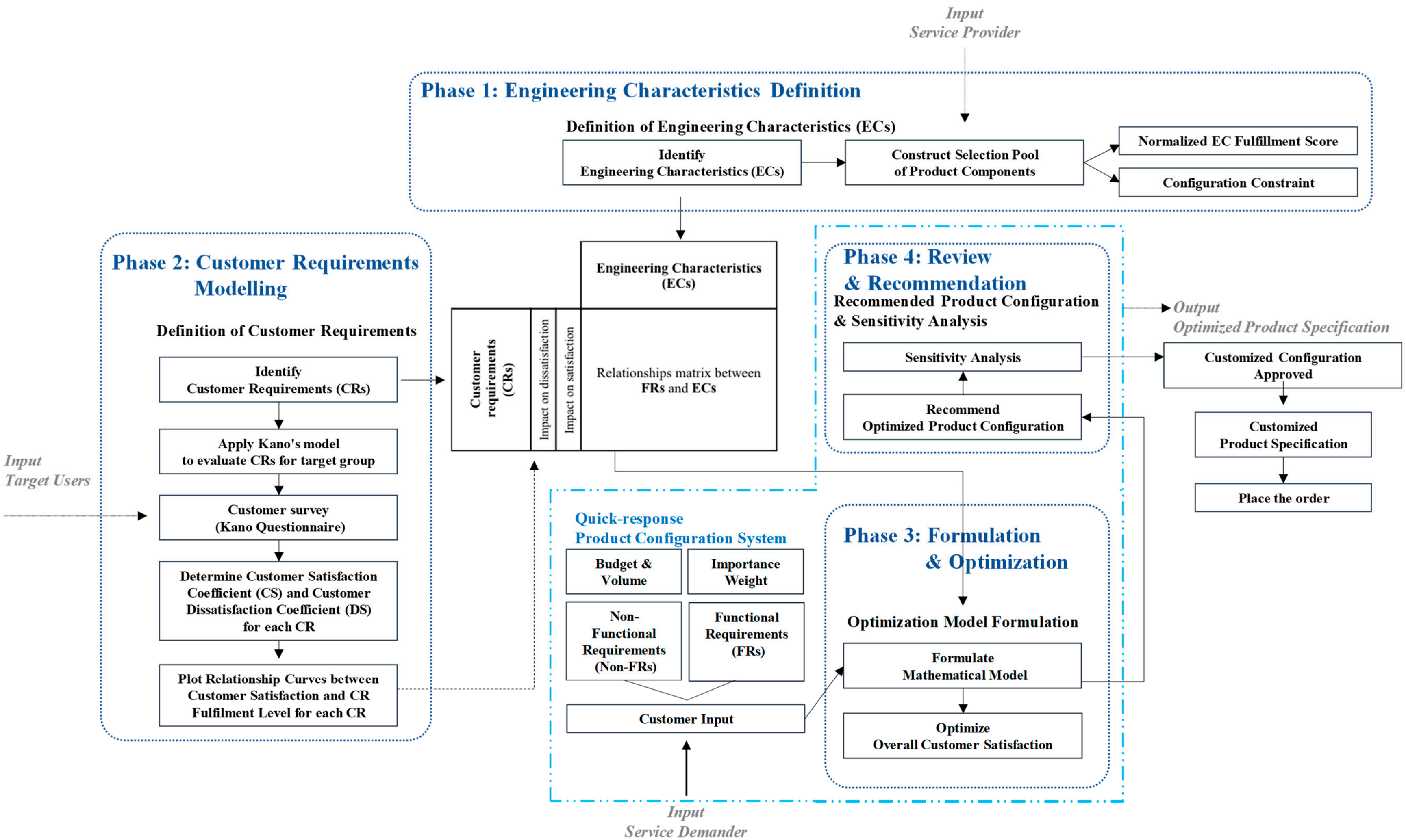

Figure 2. The design model for quick-response product configuration system.

3.1. Phase 1—Engineering Characteristics Definition: Evaluation of Enterprise Capabilities

In Phase 1, the production capabilities of an enterprise are evaluated. Engineering characteristics (ECs) are defined and selection pools are constructed based on the information collected from the service provider. Each EC has a selection pool to contain the parts that could be chosen in the configuration. Each part has a normalized EC fulfillment score and configuration constraint with other parts stated by the domain experts.

A product typically consists of multiple parts, modules, or subassembly. The ECs of a product refer to the types of parts that it has. In this study, the product configuration system focuses on only discrete ECs, i.e., the selection of parts. Technical experts help to define ECs to be involved in product configuration and define the selection pool for each EC, i.e., the set of parts can be chosen for the EC. For an EC, there could be more than one score to evaluate the performance of parts. These scores must be normalized for further analysis. In addition, configuration constraints must be known by the configuration system to avoid the recommendation of infeasible solutions.

3.2. Phase 2—Customer Requirements Modelling: Investigation of Market Demand

In Phase 2, market demand is investigated to obtain the customer preference for products. Quality function deployment (QFD) is integrated with the Kano model to qualitatively and quantitatively analyze the relationship between customer requirements (CRs) and customer satisfaction (CS) [44–47]. Satisfaction-customer requirements (S-CR) relationship functions proposed by Ji et al. [48] were used in this phase. A customer survey is conducted among the target users with a Kano questionnaire to help the construction of S-CR relationship functions, which is renamed as a customer satisfaction-Fulfillment (CS-F) relationship function [49] in this research.

Customer requirements of a product refer to the judging criteria in customer evaluation [50]. Marketing experts help to identify the CRs to be involved for the product. Then, an investigation is performed to classify the CRs into several types. Based on the investigation result, CS could be mathematically expressed by the fulfillment level of each CR and integrated into the optimization model. The ID of each CR is recorded. QFD is implemented to construct the house of quality (HOQ) [51], which is the main representation to show the relationships between ECs and CRs. A typical HOQ is shown in Figure 3.

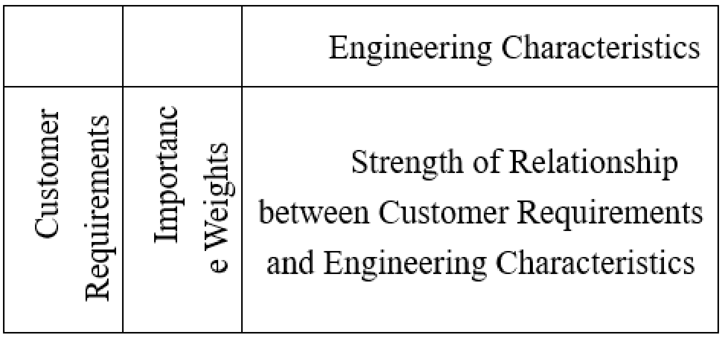

Figure 3. Typical house of quality (HOQ).

The strength of relationship has a discrete value scaled from 0 to 9, as shown in Figure 4.

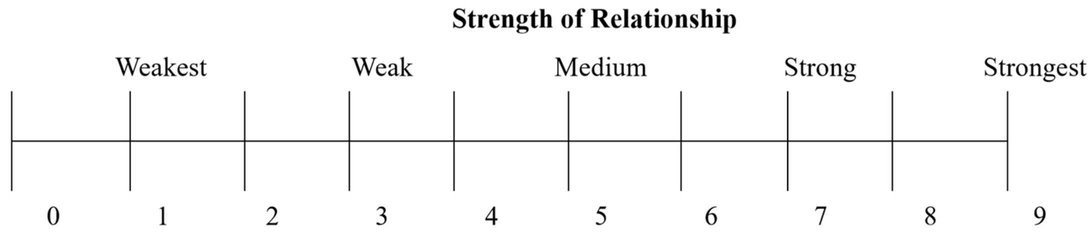

Figure 4. Scale of strength of relationship.

The strength of the relationship between CR_i and EC_j is denoted by R_{ij}, whereas $R_{ij} \in \{0, 1, 2, \ldots, 9\}$. An example of a HOQ can be written as shown in Table 1.

Table 1. Filled HOQ.

CR \ EC	A	B	C	...
1	R_{1A}	R_{1B}	R_{1C}	...
2	R_{2A}	R_{2B}	R_{2C}	...
3	R_{3A}	R_{3B}	R_{3C}	...
...	...	...	...	...

Then, R_{ij} needs to be normalized by Equation (1):

$$R'_{ij} = \frac{R_{ij}}{\sum_j R_{ij}} \quad (1)$$

(The fraction of the sum of the row in HOQ)

Thus, the normalized HOQ [52,53] can be written as shown in Table 2.

Table 2. Normalized HOQ.

CR \ EC	A	B	...
1	R'_{1A}	R'_{1B}	...
2	R'_{2A}	R'_{2B}	...
...	...	...	...

Equation (2) is always true to validate the normalized HOQ:

$$\sum_j R'_{ij} = 1 \quad \forall i \quad (2)$$

(The sum of each row is equal to 1)

R'_{ij} can be considered as the contribution of EC_j towards CR_i. The overall score of EC_j depends on its scores. It will require a fractional contribution of each score to calculate the overall score of EC_j. The fractional contribution of score m of EC_j for CR_i is denoted by $FC_{ij,m}$. Equation (3) must be always true:

$$\sum_m FC_{ij,m} = 1 \quad \forall i, j \quad for\ R'_{ij} \geq 0 \quad (3)$$

An example of $FC_{ij,m}$ can be written in a matrix as shown in Table 3.

Table 3. Fractional contribution of Engineering Characteristics- EC_A.

CR	EC_A	
	Score 1	**Score 2**
1	$FC_{1A,1} = 0.8$	$FC_{1A,2} = 0.2$
2	$FC_{2A,1} = 0$	$FC_{2A,2} = 1$

Table 3 shows that the contribution of EC_A towards CR_1 is weighted 80% on score 1 and 20% on score 2, and the contribution of EC_A towards CR_2 fully depends on score 2, i.e., score 1 of EC_A has no effect on the fulfillment of CR_2.

The normalized strength of relationship, R'_{ij} is then modified to $R''_{ij,m}$, which represents the contribution of score m of EC_j towards the CR_i. $R''_{ij,m}$ can be calculated by Equation (4):

$$R''_{ij,m} = FC_{ij,m} * R'_{ij} \tag{4}$$

The modified normalized HOQ can be written as shown in Table 4.

Table 4. Modified normalized HOQ.

EC / CR	A		B	...
	1	**2**	**1**	...
1	$R''_{1A,1} = FC_{1A,1} * R'_{1A}$	$R''_{1A,2} = FC_{1A,2} * R'_{1A}$	$R''_{1B,1} = FC_{1B,1} * R'_{1B} = R'_{1B}$	...
2	$R''_{2A,1} = FC_{2A,1} * R'_{2A}$	$R''_{2A,2} = FC_{2A,2} * R'_{2A}$	$R''_{2B,1} = FC_{2B,1} * R'_{2B} = R'_{2B}$	...
...	...	...	...	...

If EC_j has only one score, Equation (3) can be simplified to Equations (5)–(6):

$$\sum_m FC_{ij,m} = FC_{ij,1} \tag{5}$$

$$FC_{ij,1} = 1 \; \forall j, i \tag{6}$$

EC_B has only one score. Therefore, $R'_{1B,1}$ is equal to R'_{1B}, and $R'_{2B,1}$ is equal to R'_{2B}.

The fulfillment level of CR_i is denoted by F_i. For any product configuration, the EC scores can be translated to the fulfillment level of each CR by Equation (7):

$$F_i = \sum_j \sum_m S'_{j,m} R''_{ij,m} \tag{7}$$

In conclusion, this subsection constitutes the second portion of the optimization framework, as shown in Figure 5.

Normalized Strength of Relationship

Fulfillment Level

$$\begin{pmatrix} R''_{1A,1} & R''_{1A,2} & \cdots & R''_{1B,1} & R''_{1B,2} & \cdots \\ R''_{2A,1} & R''_{2A,2} & \cdots & R''_{2B,1} & R''_{2B,2} & \cdots \\ R''_{3A,1} & R''_{3A,2} & \cdots & R''_{3B,1} & R''_{3B,2} & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \end{pmatrix} \begin{pmatrix} S'_{A,1} \\ S'_{A,2} \\ \cdots \\ S'_{B,1} \\ S'_{B,2} \\ \cdots \end{pmatrix} = \begin{pmatrix} F_1 \\ F_2 \\ F_3 \\ \cdots \end{pmatrix}$$

Figure 5. Customer Requirement (CR) component in optimization framework.

This portion generates the fulfillment level of CRs as an expression of the selection of part and the normalized strength of relationship in HOQ for the subsequent process.

3.3. Phase 3—Formulation and Optimization: Build Optimization Model and Formulation

In Phase 3, a mathematical programming model is applied to formulate the overall customer satisfaction (OCS) with predefined information from the first two phases and additional input from the service demander. An optimal product configuration that maximizes OCS would be recommended.

In Phase 1, the service provider needs to define ECs with prices (P_{jk}) and scores ($S_{jk,m}$), and then normalize the scores ($S'_{jk,m}$). The normalized final score m of EC j ($S'_{j,m}$) depends on the selection of parts (X_{jk}). In Phase 2, the service provider needs to construct a HOQ with the strength of the relationship between CRs and ECs (R_{ij}) and normalize them into the normalized strength of relationship (R'_{ij}) to express the fulfillment level (F_i) by the final scores of all ECs for all CRs. Meanwhile, a Kano questionnaire must be completed to derive an expression of customer satisfaction, $CS_i = f_i(F_i, a_i, b_i)$. In Phase 3, the service demander needs to set a budget (B) and input the importance weight (w_i) for each CS. The total price of the selected parts must be no more than the budget. Overall customer satisfaction (S) can be expressed by the dot product of importance weights and customer satisfaction. The objective of the optimization model is to maximize the overall customer satisfaction under budgetary and other constraints.

By integrating all the variables, the optimization model can be formulated as shown below.

Notation:

a_i	*Constant a in $CS_i - F_i$ Relationship Function*
b_i	*Constant b in $CS_i - F_i$ Relationship Function*
B	*Budget*
F_i	*Fulfillment Level of CR_i*
CS_i	*Customer Satisfaction of CR_i*
P_{jk}	*Price of Part jk*
$R''_{ij,m}$	*Normalized Strength of Relationship between CR_i and Score m of EC_j*
S	*Overall Customer Satisfaction*
$S'_{jk,m}$	*Normalized Score m of Part jk*
$S'_{j,m}$	*Normalized Final Score m of EC_j*
w_i	*Importance Weight of CR_i in Overall Customer Satisfaction*
X_{jk}	*Selection of Part jk*

Decision Variables:

$$X_{jk} = \begin{cases} 1 & \text{if Part } jk \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$$

Objective Function:

$$\max \quad S \qquad \textit{Overall Customer Satisfaction}$$

$$\sum_k S'_{jk.m} X_{jk} = S'_{j,m} \quad \forall j \qquad \textit{Calculate Final Score m of EC}$$

$$\sum_j \sum_m R''_{ij,m} S'_{j,m} = F_i \quad \forall i \qquad \textit{Calculate Fulfillment Level of CR}$$

$$CS_i = f_i(F_i, a_i, b_i) \quad \forall i \qquad \textit{Calculate Customer Satisfaction of CR}$$

$$\sum_i w_i CS_i = S \qquad \textit{Calculate Overall Customer Satisfaction}$$

Constraints:

$$\sum_j \sum_k P_{jk} X_{jk} \leq B \qquad \textit{Total Price} \leq \textit{Total Budget Available}$$

$$\sum_k X_{jk} = 1 \quad \forall j \qquad \textit{Only one component can be selected for an EC}$$

The expression of one-dimensional CSs follows a linear function, $y = ax + b$. The expression of positive or must-be CSs follows a smooth nonlinear function, $y = ae^{x} + b$. Overall, this is a nonlinear optimization model. It cannot be solved by a linear programming algorithm. Instead, it can be solved by the generalized reduced gradient (GRG) method developed by Lasdon et al. [54]. The GRG method can be considered as a nonlinear extension of the Simplex method, which solves a linear optimization problem by selecting a basis, determining a search direction, and performing a line search on each iteration. The GRG method computes or approximates derivatives of the problem functions many times during the course of the optimization. It is robust to process the nonlinear objective function and constraints. In this research, Excel 2016 and Visual Basic for Applications (VBA) were used for the coding of the problem formulation.

3.4. Phase 4—Review and Recommendation: Sensitivity Analysis and Recommendation

In the fourth phase, sensitivity analysis is conducted for the service demander to review and determine the final customized product specification. A sensitivity analysis is performed after the optimization. It offers additional flexibility for the service demanders to review the result and adjust the output before they decide to place the orders. It looks for the nearest downgraded and upgraded configurations based on the current recommended configuration.

3.5. Quick Response Product Configuration System Design

In summary, the new product configuration system consists of backend and frontend operations. The backend operation is contributed by technical experts and marketing experts to maintain the database of configurable parts for all ECs and the effectiveness of the CS-F relationship function. Technical experts need to list the ECs and parts involved in the configuration system, with predefined scores and constraints. Marketing experts need to perform market research to understand the nature of CRs as well as how they can be fulfilled by ECs with technical experts.

The frontend operation engages the service demanders directly. They could indicate their budget, importance weight for CRs, and additional requests, if any. Once they confirm the information, the optimal solution would be presented to them with the sensitivity analysis. They could make minor adjustments or request technical support from the service provider before they place the orders. Once the orders are placed, the service provider would soon manufacture the products based on the ordered configuration and deliver them to the service demanders. Throughout this process, the product configuration system plays a vital role in bridging the communication gap and accelerating the customization process, earning a competitive edge for the service provider in Industry 4.0.

4. Empirical Case Study

The case study or simulation could be used as the "demonstration" to verify that the design approach works [55]. Furthermore, Peffers et al. [55] claimed that the feasibility of the idea can be validated using a formal evaluation (i.e., observation, survey, or interview). Thus, an empirical study for designing and developing a new product configuration system under the Industry 4.0's mass customization, high complexity, low volume ordering scenario was conducted among the supplier (main case company), service provider (company A), service demander (company B) to demonstrate the feasibility of the above proposed framework. Due to different products different product features and product specifications will reflect, in this empirical case, the manufacturing of "laptop" will be taken as an example for illustrating the design of the quick-response product configuration system as an order recommendation system to support quotation process.

4.1. Case Company's Background as a Supplier of Industry 4.0 Based Solution Provider

DT Company is a leading industrial automation manufacturer, offering efficient and reliable products and solutions to serve global customers. One of their specialties is an automated batch process for low-volume, high-complexity customization. It has had a loyal client, Company A, for years.

Company A is a business-to-business (B2B) information technology (IT) company as a supplier of Industry 4.0 based solution provider, specializing in the flexible manufacturing of desktops, laptops, and other IT devices. Established for years, Company A has been running smoothly with its standard operation procedure, including sale interviews with their clients, 'make-to-order' services, and batch production. However, recently, they have received increasingly frequent customized orders in greater diversity from their client, Company B.

Company B is a laptop retailer, which is supplied mainly by Company A. In their standard collaborative process, individual consumers visit the outlet of Company B, expressing their needs to the sales personnel of B and hoping to obtain a desirable product. If their needs are beyond the existing products available in shops, the sales personnel would inform the procurement team to place the customized order. The procurement team would then engage Company A's sales personnel for an interview to discuss the cost and feasibility of the customization. At this point, A's sales personnel would also seek technical advice from their technical personnel to validate the feasibility. Along with this communication chain, information might be misaligned sometimes. A diagram is developed to enhance the understanding of this communication chain, as shown in Figure 6.

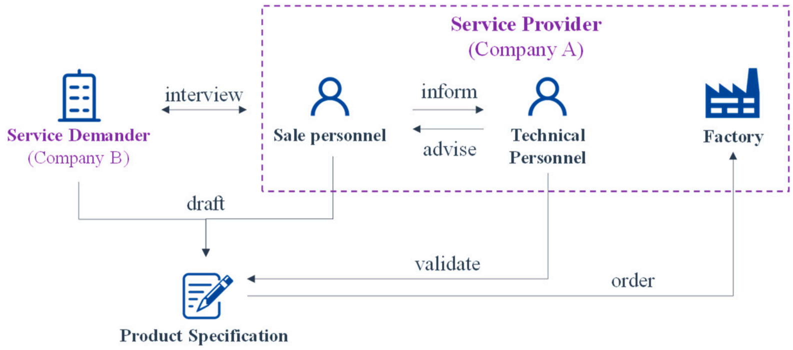

Figure 6. "As-is" model of order acquisition process.

In recent years, B has noticed that the consumer expectations have become more diverse. The communication activities between A and B had become more frequent, and thus, a more severe misalignment of information was observed. Both A and B agreed that the current process had consumed a considerable amount of manpower and showed inefficiency when the communication became more intense. They were keen to find a solution to address this issue.

In addition, Company A also noticed that there could be a communication barrier between A's sales personnel and B's procurement team. However, neither of them knew how to translate customer needs to EC's. For instance, they may want the laptop to be good at graphics processing, but they have no idea which graphics card is sufficiently capable of satisfying that need. Apparently, the best way to recommend an optimal laptop configuration is direct communication with A's technical personnel. However, this requires more manpower and incurs more workload on the technical personnel.

Therefore, Company A engaged DT Company to streamline the communication process. DT wishes to propose a recommendation system that considers the customer's evaluation priority or weight as the input to generate the optimal product configuration under the given budgetary conditions.

4.2. Data Collection

First, DT Company must evaluate the capabilities of Company A with regard to laptop configuration. Currently, Company A allows the customers to customize laptops in various ECs. In a typical customization process, a customer would first decide the primary functional components, including central processing unit (CPU), graphics processing unit (GPU), random-access memory (RAM), hard disk drive (HDD), and solid-state drive (SSD); then, they would consider the secondary functional components, including display, speaker, battery, and fan. Finally, the non-functional components, e.g., housing, including color theme and surface finish, would be addressed. An EC is denoted by EC_j, where $j \in \{A, B, C, \ldots\}$, e.g., EC_A refers to CPU, and EC_B refers to GPU. The customizable ECs are summarized in Table 5.

Table 5. ECs of Company A laptops.

EC ID	EC	Category
A	CPU	Primary Functional EC
B	GPU	
C	RAM	
D	HDD	
E	SSD	
F	Display	Secondary Functional EC
G	Speaker	
H	Battery	
J	Fan	
K	Housing	Non-functional EC

To construct the selection pool for primary functional ECs, reference data is obtained from UserBenchmark (http://www.userbenchmark.com/), which is a platform that tests and evaluates thousands of PC components with millions of benchmarks and votes. The price list of the parts for CPU, GPU, RAM, HDD, and SSD are explained in Appendix A (see Tables A1–A4).

4.3. Normalized Score

A new parameter, called 'normalized score', denoted by $S'_{jk,m}$, which represents normalized score m of Part jk, is introduced to each part. To calculate this value, the following formula is used:

$$S'_{jk,m} = \frac{S_{jk,m} - S^{min}_{j,m}}{S^{max}_{j,m} - S^{min}_{j,m}} \quad \text{if the score is positive-preferable (more is better), or}$$

$$S'_{jk,m} = \frac{S^{max}_{j,m} - S_{jk,m}}{S^{max}_{j,m} - S^{min}_{j,m}} \quad \text{if the score is negative-preferable (less is better)}$$

where $S_{jk,m}$ is the score m of Part jk, $S^{min}_{j,m}$ is the minimum score m of EC_j available in the market over the past three years, and $S^{max}_{j,m}$ is the maximum score m of EC_j that Company A possesses. Currently, all scores are positive-preferable. Therefore, only the first normalization equation is needed. The normalized score is calculated for all groups, as shown in Appendix B (See Tables A5–A9).

4.4. Customer Requirements

Based on the discussion with Company A, DT Company lists a set of CRs that conveys the common concerns of its customers, shown below:

- Price
- Business Performance (e.g., surfing, email, office work)
- Multimedia Performance (e.g., 3D gaming, professional design)
- Computation Performance (e.g., programming, big data analysis)
- Display Performance
- Audio Performance
- Battery Life
- Temperature Control

Among all the CRs, the price is used as the budgetary constraint, with the assumption that the customer intends to spend the entire budgetary amount on the best possible product configuration.

An HOQ is generated to summarize the strength of the relationships between the rest of the CRs and ECs, as shown in Table 6. The value nine denotes the strongest relationship between EC and CR, while the value zero represents a weak connection between EC and CR.

Table 6. HOQ.

CR \ EC		CPU	GPU	RAM	HDD	SSD	Display	Speaker	Battery	Fan	Housing
		A	B	C	D	E	F	G	H	J	K
Business Performance	1	9	2	1	2	5					
Multimedia Performance	2	5	9	1	3	3					
Computation Performance	3	8	4	1	3	5					
Storage	4				8	1					
Display	5						9				
Audio	6							9			
Battery Life	7								9		
Temperature Control	8									9	

For business performance, multimedia performance, and computation performance, the strength of the relationship is estimated based on a set of formulae suggested by UserBenchmark, as shown in Table 7. The normalized HOQ is generated, with critical CRs and primary functional ECs, as shown in Table 8. The modification of the fractional contribution regarding different CRs was presented in Table 9.

Table 7. Suggested evaluation criteria.

CR	Evaluation
Business Performance	50% CPU + 10% GPU + 10% HDD + 30% SSD
Multimedia Performance	25% CPU + 50% GPU + 10% HDD + 15% SSD
Computation Performance	40% CPU + 20% GPU + 15% HDD + 25% SSD

Table 8. Normalized HOQ.

CR \ EC		CPU	GPU	RAM	HDD	SSD
		A	B	C	D	E
Business Performance	1	0.47	0.11	0.05	0.11	0.26
Multimedia Performance	2	0.24	0.43	0.05	0.14	0.14
Computation Performance	3	0.38	0.19	0.05	0.14	0.24
Storage	4				0.89	0.11

Table 9. Modified normalized HOQ.

CR \ EC		CPU			GPU	RAM	HDD		SSD	
		A1	A2	A3	B	C	D1	D2	E1	E2
Business Performance	CR_1	0.379	0.047	0.047	0.11	0.05		0.11		0.26
Multimedia Performance	CR_2	0.071	0.143	0.024	0.43	0.05		0.14		0.14
Computation Performance	CR_3	0.038	0.038	0.305	0.19	0.05		0.14		0.24
Storage	CR_4						0.89		0.11	

4.5. *Application of Kano Model to Customer Requirements*

A Kano questionnaire is developed to investigate the Kano categorization, coefficient of satisfaction, and coefficient of dissatisfaction for the four critical CRs, as shown in Appendix C. For each CR, a pair of questions is asked, one in functional form and another in dysfunctional form. The questionnaire concerns customer responses regarding two extreme cases, nearly 0% and 100% fulfillment of each CR.

To formulate CS as an expression of the fulfillment level of each CR, DT Company conducted a survey among the target users of Company A's products. The survey received 120 responses. Referring to Table 10, the responses are summarized and translated to a Kano classification, as shown in Table 11. For instance, 61 respondents perceive business performance as a must-be attribute. Therefore, the Kano classification of business performance is 'M' for must-be. According to the result, customer satisfaction is formulated by the equations corresponding to the Kano classification for each customer requirement, as shown in Table 12. The customer satisfaction curves can be plotted as shown in Figure 7. The x-axis is the fulfillment level of the CR, and the y-axis is the corresponding satisfaction level.

Table 10. Recommended configuration.

EC	Selection	m	Normalized Score m, $S'_{j,m}$	Price ($)
CPU	A3	1 2 3	0.781 0.521 0.254	166
GPU	B2	1	0.286	223
RAM	C3	1	0.854	148
HDD	D4	1 2	0.25 1	86
SSD	E3	1 2	0.25 0.996	127
			Total	750

Table 11. Kano survey result.

CR	O	A	M	I	R	Q	Total	KC	CS	DS
Business Performance	20	13	**61**	26	0	0	120	M	0.275	−0.675
Multimedia Performance	**44**	25	12	29	0	0	120	O	0.658	−0.467
Computation Performance	27	**41**	14	38	0	0	120	A	0.567	−0.342
Storage	31	25	**35**	28	0	1	120	M	0.47	−0.555

O: One-dimensional; A: Attractive; M: Must-be.

Table 12. Formulation of CRs.

CR	KC	a	b	$f(x)$	$S = af(x) + b$
Business Performance	M	1.503	0.828	$-e^x$	$S = -1.503e^x + 0.828$
Multimedia Performance	O	1.125	−0.467	x	$S = 1.125x - 0.467$
Computation Performance	A	0.529	−0.87	e^x	$S = 0.529e^x - 0.87$
Storage	M	1.622	1.067	$-e^x$	$S = -1.622e^x + 1.067$

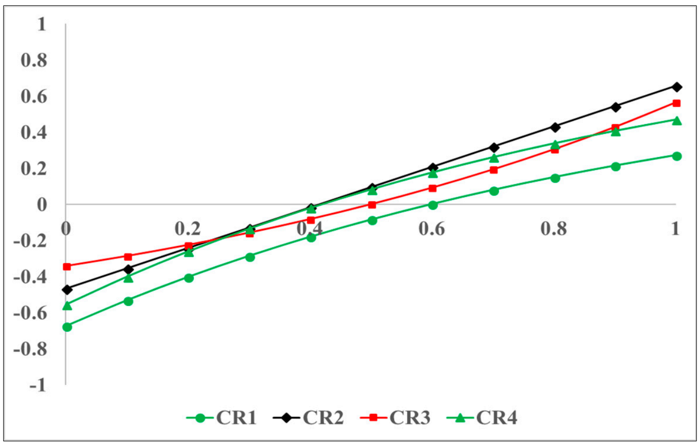

Figure 7. Customer Satisfaciton- Function (CS-F) relationship functions.

4.6. Optimization Modelling

The definition of ECs is built based on Company A's capabilities. CRs and CS-F relationship functions are built based on market research and survey. They support the backend operation of the product configuration system. Once they are ready, the system is ready to take customer inputs and recommend optimal solutions.

Company B approaches Company A to order 100 units of laptops for their customers. The expected budget is around $1000 per unit, out of which, $750 is allocated to the primary functional ECs (CPU, GPU, RAM, HDD, and SSD). The importance weight for each CR is given as shown in Table 13.

Table 13. Customer profile.

Target User	Office Clerks, White-Collar
Total Budget Allocated	750
Customer Requirement	Importance Weight
Business Performance	0.5
Multimedia Performance	0.15
Computation Performance	0.25
Storage	0.1

Based on the profile of the target user, the optimization model can be formulated below.

Decision Variables:

$$X_{jk} = \begin{cases} 1 & if\ Part\ jk\ is\ selected \\ 0 & otherwise \end{cases}$$

Objective Function:

$$max \quad S$$

Constraints:

<Total price must be no more than $750.>

$$53\ X_{A1} + 89\ X_{A2} + 166\ X_{A3} + \ldots + 216\ X_{E4} + 603\ X_{E5} \leq 750$$

<Exactly one part must be chosen from each group.>

$$X_{A1} + X_{A2} + X_{A3} + X_{A4} + X_{A5} + X_{A6} = 1$$

$$X_{B1} + X_{B2} + X_{B3} + X_{B4} + X_{B5} = 1$$

$$X_{C1} + X_{C2} + X_{C3} + X_{C4} = 1$$

$$X_{D1} + X_{D2} + X_{D3} + X_{D4} + X_{D5} + X_{D6} = 1$$

$$X_{E1} + X_{E2} + X_{E3} + X_{E4} + X_{E5} = 1$$

<Calculation of overall normalized score m ***of*** EC_j, $S'_{j,m}$***>***

$$0.521\ X_{A1,1} + 0.680\ X_{A2,1} + 0.781\ X_{A3,1} + 0.756\ X_{A4,1} + X_{A5,1} + X_{A6,1} = S'_{A,1}$$

$$0.243\ X_{A1,2} + 0.463\ X_{A2,2} + 0.521\ X_{A3,2} + 0.756\ X_{A4,2} + 0.89\ X_{A5,2} + X_{A6,2} = S'_{A,2}$$

$$0.118\ X_{A1,3} + 0.225\ X_{A2,3} + 0.255\ X_{A3,3} + 0.368\ X_{A4,3} + 0.659\ X_{A5,3} + X_{A6,3} = S'_{A,3}$$

$$0.126\ X_{B1} + 0.286\ X_{B2} + 0.563\ X_{B3} + 0.784\ X_{B4} + X_{B5} = S'_{B,1}$$

$$0.185\ X_{C1} + 0.244\ X_{C2} + 0.854\ X_{C3} + X_{C4} = S'_{C,1}$$

$$0.063\ X_{D2} + 0.125\ X_{D3} + 0.25\ X_{D4} + 0.5\ X_{D5} + X_{D6} = S'_{D,1}$$

$$0.937\ X_{D2} + 0.971\ X_{D3} + X_{D4} + 0.874\ X_{D5} + 0.73\ X_{D6} = S'_{D,2}$$

$0.125\ X_{E2} + 0.25\ X_{E3} + 0.5\ X_{E4} + X_{E5} = S'_{E,1}$

$0.998\ X_{E2} + 0.996\ X_{E3} + 0.994\ X_{E4} + X_{E5} = S'_{E,2}$

***<Calculation of fulfillment level of* CR_i, F_i>**

$0.379\ S'_{A,1} + 0.047\ S'_{A,2} + 0.047\ S'_{A,3} + 0.11\ S'_{B,1} + 0.05\ S'_{C,1} + 0.11\ S'_{D,2} + 0.26\ S'_{E,2} = F_1$

$0.071\ S'_{A,1} + 0.143\ S'_{A,2} + 0.024\ S'_{A,3} + 0.43\ S'_{B,1} + 0.05\ S'_{C,1} + 0.14\ S'_{D,2} + 0.14\ S'_{E,2} = F_2$

$0.038\ S'_{A,1} + 0.038\ S'_{A,2} + 0.305\ S'_{A,3} + 0.19\ S'_{B,1} + 0.05\ S'_{C,1} + 0.14\ S'_{D,2} + 0.24\ S'_{E,2} = F_3$

$0.89\ S_D + 0.11\ S_E = F_4$

***<Calculation of customer satisfaction level of* CR_i, CS_i>**

$-1.503\ e^{-F_1} + 0.828 = CS_1$

$1.125\ F_2 - 0.467 = CS_2$

$0.529\ e^{-F_3} - 0.87 = CS_3$

$-1.622\ e^{-F_4} + 1.067 = CS_4$

***<Calculation of overall customer satisfaction level,* S>**

$0.55\ CS_1 + 0.15\ CS_2 + 0.2\ CS_3 + 0.1\ CS_4 = S$

<Incompatibility Constraint(s)>

$X_{D1} + X_{E1} \leq 1$

4.7. Recommendation from Optimization Results

With a budget of $750, the system recommends a configuration that costs $750, resulting in an overall customer satisfaction of 0.10072. The rank of fulfillment level is the same as the rank of importance weight. It suggests that the optimization model is at least reasonable to a certain extent. After solving the optimization model by the GRG nonlinear algorithm, the optimal product configuration is obtained as shown in Table 10, with the fulfillment level and customer satisfaction level shown in Table 14, and the recommended technical parameters shown in Table 15. The recommendation also provides an upgraded solution for the customer. The sensitivity analysis presents the nearest downgraded and upgraded configurations, as shown in Table 16. The nearest downgraded configuration has an effect on SSD. It shows that SSD is the least value-added EC for the current configuration. Therefore, it should be the first to be dropped if Company B wants to reduce the budget. This corresponds with the fact that storage has the smallest weight in overall customer satisfaction. The nearest upgraded configuration affects CPU by downgrading all other ECs, showing that CPU is the most value-added EC for the current configuration. Therefore, it should be the first to be enhanced if Company B is willing to provide a larger budget. This agrees with the fact that business performance, which greatly relies on CPU, has the highest weight in overall customer satisfaction.

Table 14. Optimal fulfilment level (F) and customer satisfaction (CS).

CR	Fulfilment Level, F_i	Customer Satisfaction	Importance Weight
Business Performance	0.775	0.13561	0.5
Multimedia Performance	0.585	0.19121	0.15
Computation Performance	0.602	0.09524	0.25
Storage	0.25	−0.19587	0.1
	Overall Customer Satisfaction		0.10072

Table 15. Recommended technical parameters.

EC	Selection	Technical Parameter		
CPU	A3	Single-Core Integer Speed (pts) 114	Quad-Core Integer Speed (pts) 300	Multi-Core Integer Speed (pts) 308
GPU	B2	CLim (MHz) 1290	MLim (MHz) 1392	
RAM	C3	Capacity (GB) 2x4		
HDD	D4	Capacity (TB) 2	Sequential Read Speed (MB/s) 174	
SSD	E3	Capacity (GB) 250	Sequential Read Speed (MB/s) 497	

Table 16. Sensitivity analysis.

EC	Selection	Nearest Downgraded Configuration	Nearest Upgraded Configuration
CPU	A3	A3	**A5** #
GPU	B2	B2	*B1* *
RAM	C3	C3	*C1* *
HDD	D4	D4	*D2* *
SSD	E3	*E2* *	*E2* *
CS	0.10072	*0.09930* *	**0.10981** #
Total Price	750	*730* *	**759** #

Italic *: Decrease from the recommended configuration; **Bold #: Increase from the recommended configuration.**

4.8. OrderAssistant: A Quick-Response Product Configuration System Design

Throughout the above four phases, we can design a smart quick-response product configuration system, which is named "OrderAssistant", to assist in the response for future and expected scenarios of flexible manufacturing under Industry 4.0. OrderAssistant plays a vital role in bridging the communication gap between Company A (Manufacturer) and Company B (Customer), as well as accelerating the customization process, earning a competitive edge for both parties in Industry 4.0. Using OrderAssistant in the 'to-be' process, the production objective of "low-volume, high-complexity" order requirements can be achieved. The graphic user interface can be shown in Figure 8.

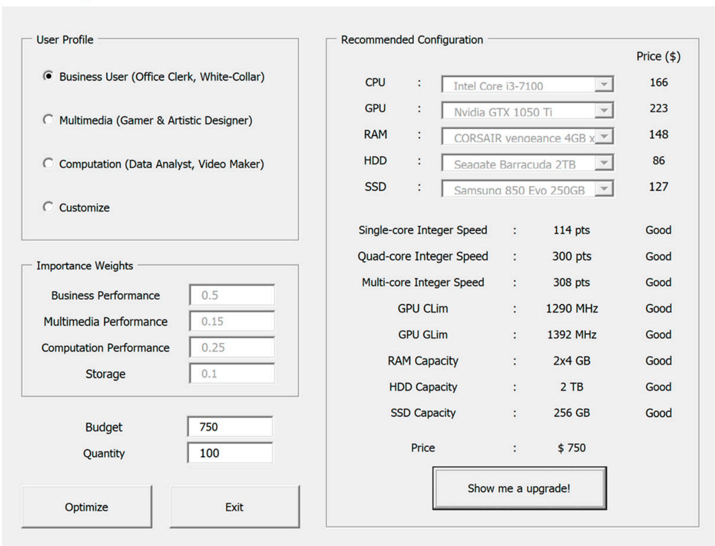

Figure 8. Graphic User Interface of OrderAssistant in formulation for optimization product configuration.

In the 'To-Be' model with OrderAssistant, Company A could respond to a customer profile given by Company B by using OrderAssistant. The customer profile includes the expected budget, importance weight of each CR, and special requests. It could generate an optimal configuration within budget immediately. Sensitivity analysis provides the nearest downgraded configuration and nearest upgraded configuration (as shown in the Figure 9) for Company B. After delivering the recommended results for the optimized product configuration for Company B, Company B could decide to place the final order for production. Finally, the order would be sent to Company A for manufacturing. The 'To-be' process is depicted and shown in Figure 10.

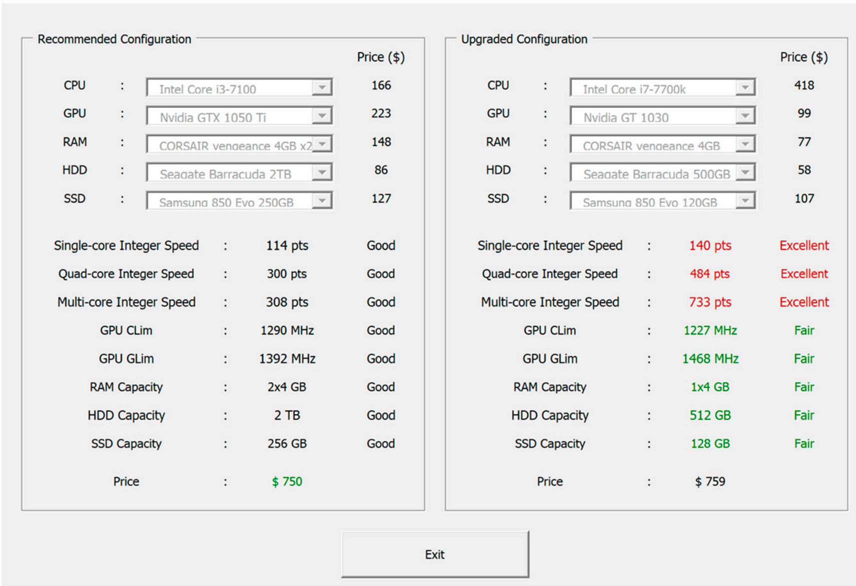

Figure 9. The upgraded recommendation of OrderAssistant based on sensitive analysis.

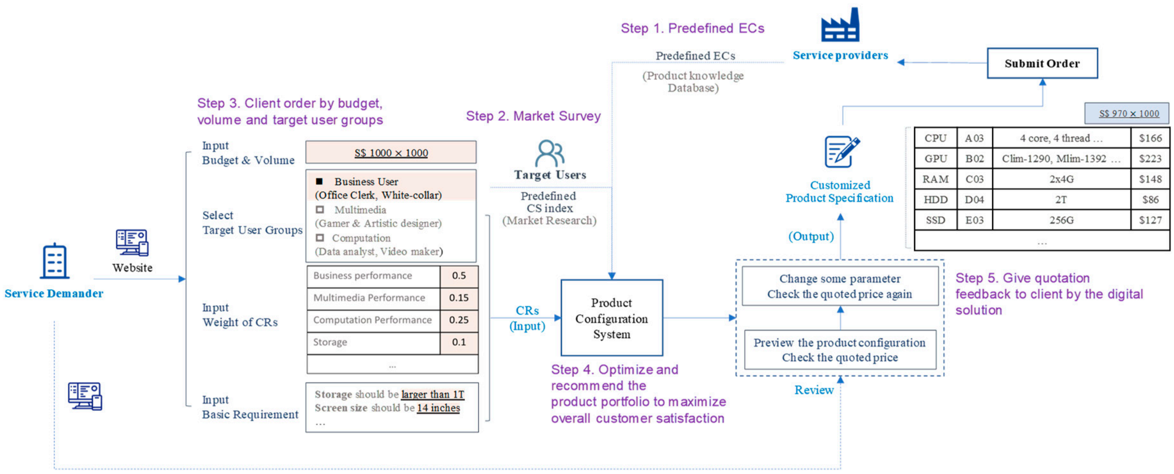

Figure 10. 'To-be' process of order acquisition and quick response process with OrderAssistant.

5. Conclusions

In the context of Industry 4.0, it is urgent for the service providers to meet dynamic customer requirements with a short response time. Thus, this study adopted a sophisticated mechanism to swiftly optimize customer satisfaction in a feasible and reasonable manner. In addition, a case study was conducted to elaborate how the product configuration system could be adopted in the order acquisition and fulfillment process for SME in the context of laptop configuration. This study helps to significantly reduce errors in the configurations released by the sales department through the implementation of the product configuration system under Industry 4.0. It is capable of handling a large volume of information exchanged between the frontend and backend departments with greater accuracy and efficiency, recovering a considerable amount of manpower spent on the traditional manual activities over the long run. Furthermore, it serves as a database to store product knowledge and all historical configurations for different user groups, accumulating intangible but valuable assets to the organization for future reference. In summary, this study provides the following contributions.

First, this is pioneering work in developing a quick response product configuration system, implementing the MTO and mass customization strategy in the context of Industry 4.0. Though Industry 4.0 enables smart manufacturing and smart factories, a product configuration system is necessary to bridge the gap between customers and manufacturers. It is expected that the proposed concept could augment the potential of Industry 4.0 in meeting dynamic user requirements.

Second, this study made a breakthrough in modifying the QFD approach. Instead of roughly considering the relationship between CRs and ECs, the authors considered the smaller elements of the relationship, reflecting on the role of EC in each CR better than before. In this way, the optimization model is robust to evaluate more than one feature for each EC and solve more practical problems.

Third, this study opens the door of using quantitative analysis, such as the Kano model or QFD approach, in the context of a product configuration system, integrating mathematical approaches into the traditional design process by presenting a customization framework on a larger scale—from product database definition to customer satisfaction quantification, optimization modelling, and finally sensitivity analysis. Pioneer work of developing a quick-response product configuration system under Industry 4.0, applying customer requirement modelling, and an optimization method was demonstrated.

Meanwhile, the novelty and advantages are summarized below:

- Engineering characteristics and voice of users are taken into consideration by the proposed design model for quick-response product configuration system in a systematic way. Thus, an in-context, customer centric, and optimization-oriented quick-response product configuration system under Industry 4.0 context was first carried out in this holistic and generalized manner.
- The empirical case study explored a real production (to-be) scenario among an international manufacturing solution supplier, a SME manufacturing service provider and a SME service demander.
- Moreover, in this scenario, the transformation between as-is process and to-be process with the new quick response product configuration system: OrderAssistant were clearly identified and described. A novel prototype developed by incorporating with Kano, QFD, and optimization model was first proposed in the research of Industry 4.0 and smart manufacturing area.

Generally, this study enriched the literature of Industry 4.0 application with the product configuration system as well as advanced a step in using integrated approaches to establish a new product configuration model. The new scenario design could be adapted and generalized in an empirical order-placement, quick-response system with product configuration recommendation.

To validate the feasibility and effectiveness of the proposed design approach, a case study of a quick response product configuration system under an industrial context and Industry 4.0 background was illustrated. The outcomes shown that the proposed design model for quick-response product configuration product configuration system approach can be a promising manner to enable design innovation in the high complexity/low volume and mass customization context effectively. However, this work, as an explorative study, still restricts its scope by only looking at a systematic process to realize the proposed design approach by an illustration of order fulfillment of the laptop. Other aspects, such as (1) virtual reality (VR) prototyping in supporting rapid product design after order handling and product specification recommendation; (2) industrial production context with more kinds of products could be explored for broadening the application scenarios of product configuration systems; and (3) in-context user experience evaluation can be further studied in-depth.

Author Contributions: C.-H.L., C.-H.C., and C.L.; methodology, X.Z.; software, C.-H.L., C.L., and F.L.; formal analysis, C.-H.L. and C.L.; investigation and data curation, C.-H.L.; writing original draft preparation, C.-H.L. and F.L.; writing—review and editing, C.-H.L. and C.-H.C.; project administration, C.-H.L. and C.-H.C.; funding acquisition.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. List Price of the Parts

Table A1. The list of parts for EC_A: CPU.

EC_A: CPU				
Part ID	**Single-Core Integer Speed (pts)**	**Quad-Core Integer Speed (pts)**	**Multi-Core Integer Speed (pts)**	**Price (S$)**
A1	83.1	161	164	53
A2	102	271	277	89
A3	114	300	308	166
A4	111	417	427	274
A5	140	484	733	418
A6	140	539	1091	475
	Score 1	**Score 2**	**Score 3**	

Table A2. The list of parts for EC_B: GPU and EC_C: RAM.

EC_B: GPU				
Part ID	**CLim (MHz)**	**MLim (MHz)**	**Score**	**Price (S$)**
B1	1227	1468	19.5	99
B2	1290	1392	38.8	223
B3	1506	1709	72.2	410
B4	1607	1683	98.9	619
B5	2025	2928	126	792
EC_C: RAM				
Part ID	**Capacity (GB)**		**Score**	**Price (S$)**
C1	1x4		38.3	77
C2	1x8		41.7	124
C3	2x4		76.4	148
C4	2x8		84.7	265

Table A3. The list of parts for EC_D: Hard disk drive (HDD).

EC_D: Hard Disk Drive (HDD)			
Part ID	**Capacity (TB)**	**Sequential Read Speed (MB/s)**	**Price (S$)**
D1	0	0	0
D2	0.5	163	58
D3	1	169	65
D4	2	174	86
D5	4	152	132
D6	8	127	252
	Score 1	**Score 2**	

Table A4. The list of parts for EC_E: Solid-state drive (SSD).

EC_E: Solid-State Drive (SSD)			
Part ID	**Capacity (GB)**	**Sequential Read Speed (MB/s)**	**Price (S$)**
E1	0	0	0
E2	120	498	107
E3	250	497	127
E4	500	496	216
E5	1000	499	603
	Score 1	**Score 2**	

Appendix B. First Normalized Score of Parts

Table A5. The list of parts for EC_A with normalized score.

EC_A: CPU						
Part ID	**Score**			**Normalized Score**		
	1	**2**	**3**	**1**	**2**	**3**
A1	83.1	161	164	0.521	0.243	0.118
A2	102	271	277	0.680	0.463	0.225
A3	114	300	308	0.781	0.521	0.255
A4	111	417	427	0.756	0.756	0.368
A5	140	484	733	1	0.890	0.659
A6	140	539	1091	1	1	1
S_{Am}^{min}	21.2	39.7	40.5			
S_{Am}^{max}	140	539	1091			

Table A6. The list of parts for EC_B with normalized score.

EC_B: GPU		
Part ID	**Score**	**Normalized Score**
B1	19.5	0.126
B2	38.8	0.286
B3	72.2	0.563
B4	98.9	0.784
B5	125	1
S_{Bm}^{min}	4.25	
S_{Bm}^{max}	125	

Table A7. The list of parts for EC_C with normalized score.

EC_C: RAM		
Part ID	**Score**	**Normalized Score**
C1	38.3	0.185
C2	41.7	0.244
C3	76.4	0.854
C4	84.7	1
$S_{C,m}^{min}$	27.8	
$S_{C,m}^{max}$	84.7	

Table A8. The list of parts for EC_D with normalized score.

EC_D: HDD				
Part ID	**Score**		**Normalized Score**	
	1	**2**	**1**	**2**
D1	0	0	0	0
D2	0.5	163	0.063	0.937
D3	1	169	0.125	0.971
D4	2	174	0.25	1
D5	4	152	0.5	0.874
D6	8	127	1	0.73
$S_{D,m}^{min}$	0	0		
$S_{D,m}^{max}$	8	174		

Table A9. The list of parts for EC_E with normalized score.

EC_E: SSD				
Part ID	**Score**		**Normalized Score**	
	1	**2**	**1**	**2**
E1	0	0	0	0
E2	122	498	0.125	0.998
E3	250	497	0.25	0.996
E4	500	496	0.5	0.994
E5	1000	499	1	1
$S_{E,m}^{min}$	0	0		
$S_{E,m}^{max}$	1000	499		

Appendix C.

Customer Survey on Personal Laptop

Part 1: Basic information

Gender: Male/Female
Age: 16 and below/16–25/26–35/36–45/46 and above
What is your major usage of laptop?

- ○ Basic Office Work (MS Word, MS PPT, Email)
- ○ Design Work (2D/3D Design, Animation, Rendering)
- ○ Gaming
- ○ Professional (Computation, Programming)
- ○ Others

Part 2: Kano Questionnaire

The objective of following questions is to test your satisfaction level when presence or absence of the described attributes when you are choosing a 'personal laptop'. All questions have the same set of options with explanations provided below. Please understand them before proceeding to the questions.

Table A10. Kano Questionnire of Customer Requirement Analysis.

1-1	If the laptop is very good at basic office work and surfing, how do you feel? *(e.g., MS Word, MS PPT, email, web browsing, video playback)*	1 2 3 4 5
1-2	If the laptop is very bad at basic office work and surfing, how do you feel?	1 2 3 4 5
2-1	If the laptop is very good at graphic processing, how do you feel? *(e.g., gaming, rendering, 2D/3D design, video editing).*	1 2 3 4 5
2-2	If the laptop is very bad at graphic processing, how do you feel?	1 2 3 4 5
3-1	If the laptop is very good at computation, how do you feel? *(e.g., programming, database, algorithm, data analysis)*	1 2 3 4 5
3-2	If the laptop is very bad at computation, how do you feel?	1 2 3 4 5
4-1	If the laptop has very large storage (>4TB), how do you feel?	1 2 3 4 5
4-2	If the laptop has very small storage (<128GB), how do you feel?	1 2 3 4 5
5-1	If the laptop has a very good at display screen, how do you feel?	1 2 3 4 5
5-2	If the laptop has a very bad at display screen, how do you feel?	1 2 3 4 5
6-1	If the laptop has a very good at audio system, how do you feel?	1 2 3 4 5
6-2	If the laptop has a very bad at audio system, how do you feel?	1 2 3 4 5
7-1	If the laptop has very long battery life (>8 hrs), how do you feel?	1 2 3 4 5
7-2	If the laptop has very short battery life (<1 hrs), how do you feel?	1 2 3 4 5
8-1	If the laptop has very good cooling system, how do you feel?	1 2 3 4 5
8-2	If the laptop has very bad cooling system, how do you feel?	1 2 3 4 5

Note: 1 = I like it that way; 2 = It must be that way; 3 = I am neutral; 4 = I can live with it that way; 5 = I dislike it that way.

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