ICED13
INTERNATIONAL CONFERENCE ON ENGINEERING DESIGN, ICED13
19-22 AUGUST 2013, SUNGKYUNKWAN UNIVERSITY, SEOUL, KOREA

THE IMPACT OF COMPLEXITY ON MANUFACTURING PERFORMANCE: A CASE STUDY OF THE SCREWDRIVER PRODUCT FAMILY

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ABSTRACT

Although many publications have addressed how to handle the increase of complexity in a modern manufacturing system, most researches have focused on complexity in either product design or production and the impact of complexity on manufacturing performance has not been clearly revealed. To complement the previous studies regarding complexity, this paper aims to investigate complexity in a manufacturing company from both product design and manufacturing perspectives and to elucidate the impact of complexity on manufacturing performance under various manufacturing conditions. Focusing on structural complexity, metrics for design and manufacturing complexity are proposed and applied to a screwdriver product family case. Then, single and multiple regression models are used to identify the impact of design and manufacturing complexity on lead time and total production cost under make-to-order and make-to-stock strategies and different demand levels. Results point to the fact that structural complexity negatively affects manufacturing performance only in the make-to-order system and the negative impact increases according to demand levels.

Keywords: design complexity, manufacturing complexity, manufacturing performace

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1 INTRODUCTION

The concept of complexity has emerged to describe a state of the world or a system within which many intricate and inter-related components exist (Norman, 2011). In this sense, complexity is an appropriately used term to describe modern manufacturing systems where various uncertainties and inter-related components exist in products and production systems (Wu et al., 2007; Zhang, 2012). Complexity tends to grow in manufacturing companies due to diverse market and business conditions causing uncertainties (Wiendahl and Scholtissek, 1994; Perona and Miragliotta, 2004).

Although complexity has been regarded as a critical issue in manufacturing systems, it is still difficult to understand and measure it. The definition of complexity is somewhat varied in literature due to the ambiguity that the term has itself (Perona and Miragliotta, 2004; Wu et al., 2007), and the concepts and metrics of complexity often depend on application areas (Crespo-Varela, 2011).

Despite the claim that complexity negatively effects manufacturing performance (Stalk, 1988), the previous research investigating this negative impact did not strongly support the belief. MacDuffie et al. (1996) found that the complexity metric indicating product commonality of all tested complexity measures only shows a negative impact on productivity; and Perona and Miragliotta (2004) failed to confirm the direct negative relationship between complexity and manufacturing performance in their empirical research.

To comprehensively understand complexity in a manufacturing system and clearly show its impact on manufacturing performance, this paper explores complexity in both product design and production (i.e., design complexity and manufacturing complexity) for a product family to understand the manufacturing consequences in an environment where product variety is sought. Based on the proposed complexity metrics in this paper, a screwdriver product family case (Park, 2005; Artar, 2008) is employed to perform regression analyses to investigate the relationship between complexity and manufacturing performance. The manufacturing performance variables included are order lead time and total production cost. These are studied under a total of six combinations across two variables: two conditions for manufacturing strategy (make-to-order and make-to-stock), and three for demand level (80K, 100K, and 120K). The aim of this paper is not only to verify the negative impact of complexity on manufacturing performance but to identify the changes in the impact of complexity under different manufacturing conditions.

2 LITERATURE REVIEW

This section reviews the literature relevant to complexity in the contexts of product design and manufacturing. Both product designs and manufacturing systems can have distinct complexity, and different complexity metrics can be used to assess their levels (Wiendahl and Scholtissek, 1994). Thus, complexity considered in this section is subdivided into design complexity and manufacturing complexity to separately discuss their definitions and metrics.

2.1 Design Complexity

Complexity in product design or engineering design, called design complexity, was explained by the Axiomatic Design Theory (Suh, 1984; Suh 1999). In this theory, design complexity is defined as a measure of uncertainty of obtaining desired functionality in a design; and the information content in a product design is a measure of complexity formulated by a logarithmic function of Information Theory (Suh, 1984; Suh 1999). Similar to Suh's definition of design complexity, Braha and Maimom (1998) defined design complexity based on Information Theory and categorized design complexity into two types: (1) Structural Design Complexity, defined as "a function of the design's information contents" (Braha and Maimon, 1998, pp. 528), and (2) Functional Design Complexity, represented as "a function of [relevant] probability of successfully achieving the required specifications" (Braha and Maimon, 1998, pp. 528). Design complexity was also described by interactions among components in a product. Rodriguez-Toro et al. (2004) considered design complexity from the structural property of a system or product which is related to the number of components, interactions among components, and relationships with other design properties. Crespo-Varela et al. (2011) viewed design complexity as the degree of difficulty to achieve required functions and relationships among components in a device.

With the effort to understand complexity in product design, complexity has been measured to provide objective information for determining better product designs. Pahl and Beitz (1996) proposed qualitatively measuring the simplicity of a product design from product shapes and design factors as the opposing concept of complexity.

Most direct design complexity measures were inspired by Information Theory; and these measures tried evaluating the amount of information a certain product has (Suh 1984; Braha and Maimom 1998; El-Haik and Yang, 1999). On the other hand, Bashir and Thomson (1999) proposed a direct design complexity measure based on the decomposed functions and their levels in the functional tree of a product. Similarly, Ameri et al. (2008) developed two design complexity measures by considering not only entropy in the structure of a product but also functional connectivity among its components.

Design complexity also has been discussed as the inverse indicator of commonality among products. Collier (1981) created the Degree of Commonality Index (DCI) to estimate average commonality between different types of end products. Wacker and Treleven (1986) proposed various types of commonality indices derived from DCI and revised the cardinal measure of DCI to the relative measure with an absolute range (0 to 1) of the proposed indices. Martin and Ishii (1997) developed a set of quantitative and qualitative tools including DCI and the plots to show commonality of components for production processes. Johnson and Kirchain (2010) proposed four commonality indices for a product family by considering production volumes as well as the number of shared components. Roy et al. (2011) devised the Design Ratio to analyze commonality of each part variant in a product family.

2.2 Manufacturing Complexity

A manufacturing system handling multiple products is also influenced by complexity in its production processes since a high variety of products and their components in a manufacturing system basically requires numerous machines with different functions and multiple processes. For example, even if a product is not complex in design, it might need to pass through multiple and varied processes. A manufacturing system may be more vulnerable to complexity than a product because of customer requirements (e.g., demand and lead time), manufacturing constraints and variable states of each machine. Thus, manufacturing complexity, representing complexity in a manufacturing system, should be simultaneously considered with design complexity to properly capture complexity occurring from product design and manufacturing in a company.

Manufacturing complexity can be divided into static (structural) and dynamic (operational) complexity (Frizelle and Woodcock, 1995; Deshmukh et al., 1998). Static complexity refers to complexity caused by the structural configuration of a manufacturing system, and dynamic complexity is induced by uncertainty due to the variability of a manufacturing system in a time period (Deshmukh et al., 1998).

In contrast to design complexity discussed from various perspectives, most measures of manufacturing complexity have been quantified through an information (entropy) theoretic approach. Frizelle and Woodcock (1995) defined the static and dynamic complexity measures emphasizing the entropy in a manufacturing system, determined by the inventory queues of each machine at its operational states. Deshmukh et al. (1998) also defined a static complexity measure to calculate the information held in a manufacturing system by considering the processing times of a part mix for each operation at required machines. Fujimoto et al. (2003) proposed an entropic measure of manufacturing complexity for a product family, reflecting product variety and its impact on assembly processes. Hu et al. (2008) developed a unified measure of manufacturing complexity aggregating product variety and assembly process information for supply chains as well as assembly systems. Zhang (2012) emulated an entropy model to define static and dynamic manufacturing complexity for job scheduling in a manufacturing system.

3 METHODOLOGY

Both design and manufacturing complexity can be summarized by two perspectives of complexity as per our literature review: static and dynamic complexity. Static design and manufacturing complexity considers the structure or configuration in a product and production system, which is time-independent, whereas dynamic design and manufacturing complexity represents functional and manufacturing variation among elements over time. In both cases of complexity (i.e., design and manufacturing), the static aspect focuses on deterministic structural size of a system (e.g., the number of elements or interactions) by decomposing it into single elements. This static approach to complexity measures uncertainty occurring from the magnitude of a structure. On the other hand, the dynamic approach to complexity reflects the state changes of a system, and considers time-dependent activities increasing complexity in a system.

All the complexity metrics introduced in the literature review have aimed to properly capture complexity in design or manufacturing from their own perspectives. However, most design complexity metrics, except the metrics relevant to commonality, focused on individual products; thus, they would not be suitable to reflect current high product variety trends and product family cases. Although recently proposed manufacturing complexity metrics consider integrating both product variety and manufacturing attributes, they tend to use solely the information theoretical approach requiring several assumptions and *a priori* information (Fujimoto et al, 2003; Hu et al, 2008; Zhang, 2012).

Frequently used product family based production systems might possess distinct properties in complexity; common parts and shared manufacturing processes on a common platform would decrease complexity, and variations on the common platform would result in complexity. Also, more simple and straightforward metrics for design and manufacturing complexity are needed for practical use in company settings.

Despite the widespread belief that increasing complexity in a product design or manufacturing system causes unavoidable indirect and direct costs (Wu et al., 2007), previous literature investigating this relationship has not been decisive due to the use of unsuitable complexity metrics and the lack of statistical analysis. Moreover, the lead-time of a product has not been considered as an impact of complexity; instead, previous research mainly explored the impact of complexity on productivity and cost (e.g., Randall and Ulrich, 2001; Perona and Miragliotta, 2004). For these reasons, this paper proposes practical complexity measures in design and manufacturing complexity for a product family, and analyzes how design and manufacturing complexity affect the total production cost and lead-time of a product family through a case study. For the illustration, a product family of five power screwdrivers presented by Park (2005) is employed to derive design and manufacturing complexity values. Then, the impact of complexity on manufacturing performance is analyzed by using Artar (2008)'s screw driver product family simulation results, which contain the order lead time and total production cost of the manufacturing system handling individual screwdriver orders or mix-product orders with two different product types under different manufacturing strategies (i.e., make-to-order and make-to-stock) and demand levels (80K, 100K, and 120K). The subsections specified below present the three main steps performed for this study.

3.1 Review and Determination of Complexity Metrics

Suitable complexity metrics for the screwdriver product family case are examined from all design and manufacturing complexity metrics introduced in the literature review section. Since the information of the part variants and the major manufacturing processes, presented through a set of bill of materials (BOM) (Park, 2005; Artar, 2008), are the only available input data for complexity metrics, the complexity metrics reflecting dynamic complexity are not investigated. Focusing on examining the static complexity metrics, only Roy et al. (2011)'s part commonality measure was found to be partly applicable to measure design complexity of the screwdriver product family. Given the information of the product family, there is no proper manufacturing complexity because all the manufacturing complexity metrics are based on the information theoretic approach.

3.2 Development and Application of Complexity Metrics

Roy et al. (2011)'s complexity metric is an indirect measure and calculates the commonality of each part in a product family, so the original metric should be revised into a direct complexity measure for each product or manufacturing order. For manufacturing complexity, a new metric, inspired by Wacker and Treleven (1986)'s metric, is created by considering the processed parts in each manufacturing process.

3.2.1 Design Complexity Metric

Roy et al. (2011)'s design complexity metric, Design Ratio, is shown in Equation 1.

$$\text{Design Ratio } (DR_i) = n_i / n \tag{1}$$

where n_i is the number of product variants that use part variant i and n is the total number of product variants. This indirect metric can be transformed into a direct measure, Complexity Ratio, as the following equation (Crespo-Varela, 2011):

$$Complexity\ Ratio\ (CR_i) = 1 - (n_i / n) \quad (2)$$

The design ratio of a part variant represents how many product variants can share a particular part variant. The design ratio has a range from 0 (the highest complexity) to 1 (the lowest complexity). In the case of the screw driver product family, the product variants are the five types of screwdrivers consisting of the different combinations of components. Expanding the concept of product variants, we also regard different types of assembly orders as individual product variants. At the stage of manufacturing, a production order may have different combinations of product variants. This order variant can be also viewed as an artificial product variant consisting of all the components used in the products of the order. Since the screwdriver manufacturing system has only two types of orders, individual product and a pair of products, the screwdriver product family is considered as 15 product variants, 5 individual product variants: P1, … , P5 and 10 artificial product variants (product pairs): P6 = (P1 & P2), … , P15= (P4 & P5).
The following steps are performed to derive the design ratio and complexity ratio.

- All part variants of all product variants on the BOMs are listed in rows. The part variants of each part type are identified by the different dimensions of the part type.
- All possible product variants including artificial product variants are specified in columns. After making the part-product matrix, if the original five screwdriver variants require certain part variants, 1 is assigned in the corresponding cells to indicate the usage of the part variants. 1 is also assigned to the part variants of each artificial product variant by 'OR' logic between the assigned values of the members of each artificial product variant (see Table 1). The values assigned for artificial product variants also reflect the usage of the relevant part variants.

Table 1. Example of an artificial product variant

Part Name	Variant	P1	P2	P3(P1&P2)
Bit	L=63.5 / D=6.3	1	1	1 OR 1 = 1

- The sum of each row is n_i. The complexity ratio of each part variant is computed by Equation 2.

Unfortunately, Roy et al. (2011) did not present how to compute the total commonality of each product variant. Instead, Crespo-Varela (2011) proposed a summation and multiplication model to obtain the aggregated commonality of each product variant from summing and multiplying the design ratios. Since the multiplication model unconditionally would result in the complexity value close to 1 if there are many part variants, a summation and average model to compute an aggregated complexity ratio are chosen as two possible options for design complexity (see Equations 3 and 4). The summation model is normalized by the total sum of the complexity ratios to maintain a range of 0 to 1.

$$Additive\ Model:\ Design\ Complexity\ of\ Product\ Variant\ j = \sum_{i=1}^{n_j} CR_i \ / \ \sum_{k=1}^{n} CR_k \quad (3)$$

$$Average\ Model:\ Design\ Complexity\ of\ Product\ Variant\ j = \sum_{i=1}^{n_j} CR_i \ / n_j \quad (4)$$

where, j = 1, … , 15 (product variants), i = 1, … , n_j (part variants in j), and k = 1, … , n (part variants)

3.3.2 Manufacturing Complexity Metric

Most manufacturing complexity metrics provide the total complexity value of an entire manufacturing system rather than the individual complexity value of each product in a product family. Therefore, a manufacturing complexity metric is created to be able to obtain the individual manufacturing complexity levels of product variants; this metric is inspired by Waker and Treleven (1986)'s Total Constant Commonality Index (TCCI). Three models are developed by focusing on commonality of each manufacturing processes (see Equation 5-7).

$$Average\ Model:\ Manufacturing\ Complexity\ of\ Product\ Variant\ j = \sum_{i=1}^{P_j} (1/\varphi_{ij}) / \ P_j \quad (5)$$

$$Additive\ Model:\ Manufacturing\ Complexity\ of\ Product\ Variant\ j = \sum_{i=1}^{P_j} (1/\varphi_{ij}) \quad (6)$$

$$Multiplicative\ Model:\ Manufacturing\ Complexity\ of\ Product\ Variant\ j = \prod_{i=1}^{P_j} (1/\varphi_{ij}) \quad (7)$$

where, φ_{ij} is the number of part variants passing through i^{th} process for j^{th} product variant, and p_j is the number of required processes for j^{th} product variant. The above manufacturing complexity models are based on the same component ($1/\varphi_{ij}$), indicating the level of part commonality of each manufacturing process. The average and additive models for manufacturing complexity imply the same meaning: the more processes and the less part variety a system or each process handles, the higher manufacturing complexity there is since more manufacturing processes are needed to deal with relatively low part variety. However, the multiplicative model reflects that high part variety in each process may cause the increase in setups and uncertainties to deal with parts and thereby increasing complexity in manufacturing. The additive model generates complexity values having no boundaries (a greater value implies a higher complexity), but the average model maintains the same absolute boundaries: 0 (the lowest) to 1(the highest) as the design complexity models. The multiplicative model has the same boundaries but with inverse meaning: 0 (the highest) and 1 (the lowest) because the multiplication of fractions alters originally increasing monotonicity into decreasing monotonicity.

3.3.3 Validation of Complexity Metric

The proposed metric models of design and manufacturing complexity are all static, structural complexity models. Thus, if the metrics were appropriately developed, they would be highly correlated with the structural properties of product designs and manufacturing systems. Based on this idea, the correlations between the design and manufacturing complexity models and the number of part variants and the number of processes for each product variant are investigated (see Table 2). Within each category (design and manufacturing) of complexity models, the metric model with the highest correlation is selected as the most applicable model for design and manufacturing complexity.

Table 2. Structural Size of Each Product Order Type

Product Type	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
# of Part Variants	17	22	24	41	42	32	35	55	57	29	61	61	64	64	48
# of Processes	2	3	3	4	4	3	3	4	4	3	4	4	4	4	4

3.3 Regression Analysis for the Impact of Complexity

After obtaining design and manufacturing complexity values for each product variant (or order type), the impacts of design and manufacturing on the lead-time and total production cost of the screwdriver product family are analyzed by single and multiple linear regression models (see Equations 8 and 9).

$$\textit{Single Regression Model:} \quad Y = \beta_0 + \beta_1 X \tag{8}$$

$$\textit{Multiple Regression Model:} \; Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \tag{9}$$

where Y is manufacturing performance, X is design or manufacturing complexity, X_1 is design complexity, and X_2 is manufacturing complexity. The response variables of the single and multiple regression analysis are six different lead-time and total production cost combinations of the 15 order types according to the scheduling strategies (make-to-order and make-to-stock) and demand quantities (80K, 100K, and 120K), and the predictors are design and manufacturing complexity of the 15 order types. The make-to-order strategy is a strategy to start manufacturing only when orders arrive. In contrast, the make-to-stock strategy is producing common parts regardless of order arrivals and holding them in inventory. The performance measures under different manufacturing conditions allow us to identify how the impacts of design and manufacturing complexity on the manufacturing performances vary according to the manufacturing environments. To identify the change in the impact of complexity according to demand levels, 80K and 120K are compared for the analysis since only these two demand levels were simulated with the same distribution in Artar (2008)'s work. The following hypotheses are examined through regression analyses.

- Both design and manufacturing complexity increase total production cost and order lead-time.
- The impact of complexity can be differently controlled by manufacturing strategies.
- Order demand can affect the impact of complexity on manufacturing performance.

4 RESULTS

From the design and manufacturing complexity (DC and MC) models discussed in the methodology section, the following complexity values were obtained (see Table 3).

Table 3. Design and Manufacturing Complexity

Product Variant	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15

Additive DC	0.19	0.20	0.25	0.43	0.44	0.36	0.41	0.61	0.63	0.32	0.63	0.64	0.68	0.69	0.54
Average DC	0.44	0.36	0.41	0.41	0.42	0.45	0.47	0.44	0.44	0.43	0.41	0.41	0.42	0.42	0.44
Average MC	0.27	0.51	0.50	0.56	0.44	0.51	0.50	0.56	0.44	0.50	0.56	0.44	0.56	0.44	0.44
Additive MC	0.53	1.53	1.50	2.25	1.74	1.53	1.50	2.25	1.74	1.50	2.25	1.74	2.25	1.74	1.74
Multiplicative MC	0.07	0.07	0.06	0.02	0.01	0.07	0.06	0.02	0.01	0.06	0.02	0.01	0.02	0.01	0.01

The initially developed complexity models were validated through correlation analysis with the structural sizes of the product variants in design and manufacturing (see Table 4). From the correlation results, the additive model of design complexity and the multiplicative model of manufacturing complexity were finally selected.

Table 4. Correlation between Structural Sizes and Complexity Metrics

Cases	Additive(DC)	Average(DC)	Additive (MC)	Average (MC)	Multiplicative (MC)
Correlation	0.99	0.05	0.86	0.45	-0.93

Figure 1 shows the single regression results between the manufacturing performance measures under different manufacturing scenarios and using the pre-determined design and manufacturing complexity metrics.

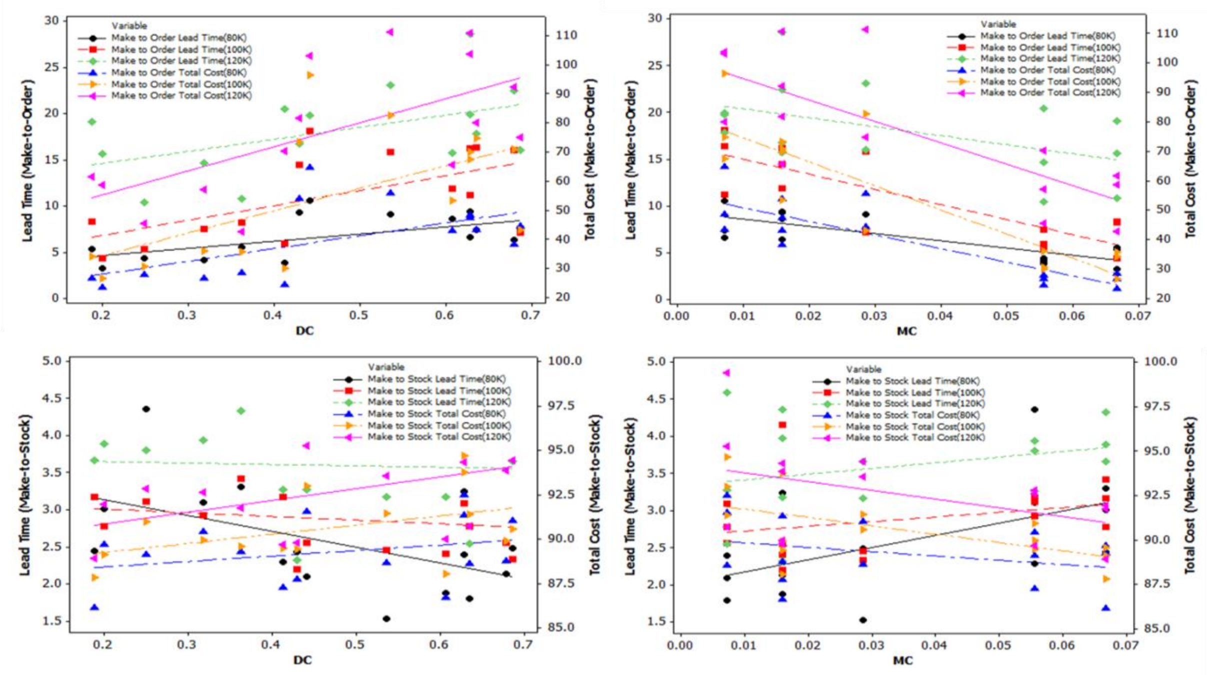

Figure 1. Single Regression for Manufacturing Performance on Complexity

It is seen that (Table 5) design complexity is a significant predictor of the lead-time (LT) and the total cost (TC) in all the scenarios at the 90% confidence, and all regression models except the make-to-order lead time (120K) show that design complexity is a significant predictor at the 95% confidence. Design complexity shows a negative impact on the manufacturing performances due to its positive coefficient in each regression model. Moreover, the coefficients of design complexity tend to increase when demand increases from 80K to 120K. However, all the single regression models show very low R^2 values, so the manufacturing performances cannot be properly predicted from design complexity.

Table 5. Manufacturing Performance under Make-to-Order on Design Complexity

Scenarios	LT (80K)	LT (100K)	LT (120K)	TC (80K)	TC (100K)	TC (120K)
Equation	y = 3.13 + 7.74x	y = 3.6 + 16.1x	y = 12.0 + 13.1x	y = 19.2 + 44.0x	y = 18.9 + 7.72x	y = 38.4 + 83.1x
R-sq	34.5%	36%	23.9%	35.0%	35.9%	41.0%
Test for β	p= 0.021**	p= 0.018**	p= 0.064*	p= 0.020**	p = 0.018**	p = 0.010**

*: $\alpha < 0.1$, **: $\alpha < 0.05$

Table 6. Manufacturing Performance under Make-to-Order on Manufacturing Complexity

Scenarios	LT (80K)	LT (100K)	LT (120K)	TC (80K)	TC (100K)	TC (120K)

Equation	y = 9.36 – 76.9x	y = 16.6 – 161x	y = 21.3 - 96.0x	y = 55.4 - 462x	y = 82.7 – 817x	y = 102 – 728x
R-sq	64.0%	67.7%	24.3%	72.5%	75.5%	59.0%
Test for β	p= 0.000**	p= 0.000**	p= 0.062*	p= 0.000**	p = 0.000**	p = 0.001**

In Table 6, all the single regression models with manufacturing complexity have higher R^2 values than those in Table 8. However, each regression model in the 120K demand of the lead time and the total production cost has the lowest R^2 value. Manufacturing complexity is a significant variable at the 95% confidence level except for the make-to-order lead time (120K) case; and at the 90% confidence level, for all the regression models. Although the coefficients of manufacturing complexity in all the regression models have negative values, these also indicate the negative impact of manufacturing complexity due to the inverse meaning of the manufacturing complexity boundaries. The slope of manufacturing complexity becomes stiff as demand increases from 80K to 120K, implying that an increase in demand leads to more negative impact.

Table 7. Manufacturing Performance under Make-to-Stock on Design Complexity

Scenarios	LT (80K)	LT (100K)	LT (120K)	TC (80K)	TC (100K)	TC (120K)
Equation	y = 3.56 – 2.14x	y = 3.11 – 0.49x	y = 3.69 – 0.19x	y = 87.8 + 3.10x	y = 88.2 + 5.10x	y = 89.5 + 6.65x
R-sq	26.7%	2.9%	0.3%	8.6%	20.4%	18.4%
Test for β	p= 0.049**	p= 0.541	p= 0.857	p= 0.290	p = 0.091*	p = 0.110

Table 8. Manufacturing Performance under Make-to-Stock on Manufacturing Complexity

Scenarios	LT (80K)	LT (100K)	LT (120K)	TC (80K)	TC (100K)	TC (120K)
Equation	y = 2.01 + 16.4x	y = 2.66 + 6.29x	y = 3.34 + 7.65x	y = 90.1 – 24.4x	y = 92.2 – 46.9x	y = 94.3 – 49.5x
R-sq	29.5%	9.0%	8.2%	10.0%	32.5%	19.2%
Test for β	p= 0.036**	p= 0.277	p= 0.3	p= 0.250	p = 0.027**	p = 0.103

However, all the single regression models in the make-to-stock case are not suitable to estimate the manufacturing performances (see Tables 7 ~ 8). In all the scenarios, the R^2 values are less than 30%. In addition, design complexity is significant at the 95% confidence level only for the make-to-stock lead time (80K), and manufacturing complexity is at a significant level only for the make-to-stock lead time (80K) and make-to-stock total cost (100K). The coefficients of design and manufacturing complexity in the make-to-stock lead time (80K) case show their positive impact on the lead time, which is different from our hypothesis. However, the negative impact of complexity is still maintained in the make-to-stock total cost (100K) case. Overall, it seems that design and manufacturing complexity are not closely related to the make-to-stock manufacturing performances.

Table 9. Manufacturing Performance under Make-to-Order on DC and MC

Scenarios	LT (80K)	LT (100K)	LT (120K)	TC (80K)	TC (100K)	TC (120K)
Equation	y = 11.3 – 2.84x1 – 93.9x2	y = 20.8 – 6.26x1 – 199x2	y = 16.7 + 6.9x1 – 54.7x2	y = 71.8 – 24.5x1 – 608x2	y = 113 – 45.4x1 – 1088x2	y = 99.6 + 3.6x1 – 706x2
R-sq	65.5%	69.5%	26.5%	76.0%	79.6%	59.1%
Test for β_1	p= 0.483	p= 0.421	p= 0.562	p= 0.208	p = 0.149	p = 0.933
Test for β_2	p= 0.006**	p= 0.003**	p= 0.530	p= 0.001**	p= 0.000**	p= 0.040**
Test Model	p = 0.002**	p = 0.001**	p = 0.158	p = 0.000**	p = 0.000**	p = 0.005**

Table 10. Manufacturing Performance under Make-to-Stock on DC and MC

Scenarios	LT (80K)	LT (100K)	LT (120K)	TC (80K)	TC (100K)	TC (120K)
Equation	y = 2.61 – 0.89x1 + 11.0x2	y = 2.22 + 0.66x1 + 10.3x2	y = 1.95 + 2.07x1 + 20.1x2	y = 89.4 + 1.06x1 – 18.1x2	y = 92.6 – 0.58x1 – 50.4x2	y = 92.1 + 3.31x1 – 29.6x2
R-sq	31.0%	10.7%	18.6%	10.4%	32.6%	20.7%
Test for β_1	p= 0.617	p= 0.639	p= 0.238	p= 0.838	p = 0.904	p = 0.644
Test for β_2	p= 0.400	p= 0.326	p= 0.125	p= 0.633	p= 0.166	p= 0.571
Model Test	p = 0.107	p = 0.506	p = 0.290	p = 0.519	p = 0.094*	p = 0.249

Tables 9 and 10 show the multiple linear regression results. In the make-to-order case (see Table 9), design complexity in all the regression models is not a significant linear predictor at the 95% confidence level when it is added to the model with manufacturing complexity. On the other hand, manufacturing complexity is significant at the 95% confidence level in all the manufacturing performance cases except for the make-to-order lead time (120K). The coefficients of the statistically significant manufacturing complexity variables in the multiple regression models support the negative impact of manufacturing complexity and the worsened negative impact of complexity subject to a demand increase.

In Table 10, none of the multiple regression models is suitable to predict manufacturing performance in the make-to-stock manufacturing system; models are not statistically significant at 95% confidence and the R^2 values are very low. The consistent negative impacts of design and manufacturing complexity are not found due to the varying signs of the design and manufacturing complexity coefficients in the multiple regression models. Thus, it can be inferred that the impact of complexity is not directly related to the manufacturing performance in the make-to-stock case.

5 CONCLUSIONS & FUTURE WORK

In this paper, static complexity metrics for design and manufacturing complexity were proposed to identify how the concept and degree of complexity can be separately considered in the design and manufacturing aspects for a product family. Through a screwdriver product family case, we validated several possible models for design and manufacturing complexity metrics, and the additive model of design complexity, revised from the Design Ratio, and the multiplicative model of manufacturing complexity, inspired by TCCI, were determined from the correlation analysis between the structural size of the product family's products and manufacturing system.

The relationships between manufacturing performance and complexity under different demand levels and scheduling strategies were further observed through single and multiple linear regression analyses. For this, the simulation results (lead-time and total production cost) of the screwdriver product family presented by Artar (2008), which were performed under different manufacturing scenarios of demand (80K, 100K, and 120K) and manufacturing strategy (make-to-order vs. make-to-stock), were employed. As a result, the negative impacts of design and manufacturing complexity on lead-time and total production cost were found to be statistically significant under the make-to-order strategy, and their deteriorating impacts according to the increase in demand were observed. However, these relationships were not identified for the case of the make-to-stock strategy.

Notably, this result is contrary to the experimental results conducted by Wu et al. (2008), concluding that operational (dynamic) manufacturing complexity is only associated with the operational costs in the make-to-stock case. It seems that the differences occur from the different perspectives of the complexity metrics. The static and structural aspects of complexity are contemplated for the complexity metrics in this paper, but the operational complexity in Wu et al. (2008)'s paper reflects the uncertainties caused by dynamic state changes in manufacturing processes. The dynamic complexity in Wu et al. (2008)'s paper might have not properly captured possible static complexity in a make-to-order system, which holds no inventory and thus is more static than a make-to-stock system. Similarly, the make-to-stock system for the screwdriver product family continuously producing common parts and storing them in inventory would have decreased static design and manufacturing complexity, and the make-to-stock system could have been identified by dynamic complexity. These findings suggest that both the static and dynamic aspects of complexity measures should be implemented to correctly identify all possible complexity in a manufacturing system. In the future, both static and dynamic complexity should be simultaneously analyzed in make-to-order and make-to-stock cases to confirm their relationships.

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