A Case Study Measuring the Impact of a Participatory Design Intervention on System Complexity and Cycle Time in an Assemble-to-Order System

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Abstract
The literature identifies that a better understanding of the relationship between people and complexity in assembly design and operation is needed. This need is studied here with an industrial case study and by employing a socio-technical approach: assembly system operators are invited to take an active role in the participatory design of an assemble-to-order system. To measure the impact of the design intervention, a before versus after comparison is made. The investigative process begins with 371 observation samples; elementary units of the cycle time population are tested with Welch’s ANOVA and regression into complexity variables and a complexity ratio. The complexity ratio is correlated to cycle time with regression (R-sq>0.75, 95% confidence), highlighting improved complexity organization with the “after” working design strategy. The observation models are used to predict theoretical complexity ratios and cycle times for direct comparison with a paired t-test. In the case study, the participatory design intervention proves significant by decreasing mean cycle time by 0.72 min/assembly. Based on these results, the investigative process proves useful in assessing assembly system complexity relative to a working design (complexity ratio) and mean cycle time.

Keywords: assembly complexity, socio-technical design, participatory design, case study, assemble-to-order

1 Introduction

A summary of the literature on complexity in engineering design and manufacturing concluded that there is a critical need for engineers and businesses to innovate and manage complex socio-technical systems (ElMaraghy et al., 2012). Further, an assessment of manufacturing operational complexity determined that, “The manufacturing system must balance human characteristics, needs, skills and capabilities within the technical and business environment, in order to be effective and successful” (ElMaraghy & Urbanic, 2004, p. 401). This human side of manufacturing is also emphasized in a summary of the literature on complexity in assembly systems arising from product variety, which
found that “Many assembly operations are so complex that human assembly workers are the most efficient solution. In some cases, manual operations are the only options” (Hu et al., 2011, p. 726). Fisher, Jain, and MacDuffie (1995, p. 125) note that to respond to product variety in assembly systems, it’s critical to consider “the way that human skills are organized” as a priority. Given these findings, and the projection that product variety will increase in the growing paradigm of manufacturing customization (Koren, 2010), a better understanding of the relationship between people and assembly system complexity in design and operation is needed.

The blend of human and technical aspects is characteristic of a socio-technical system, which is defined when workers are operators, not just users, of and within a system (Vermaas et al., 2011, p. 70). In turn, the actions of the operators shape the assembly system, particularly when it is manual. This places system operators in a unique complexity position – influencing the system with their actions and receiving system feedback that results from their actions. The experiences and tacit knowledge of the operators within an assembly system are thus essential to understanding its operation and the effectiveness of its design, which can be directly addressed by inviting assembly operators to participate in the design process. Participatory design is a socially guided design process, wherein stakeholders take action and engage with the designers in mutual learning (Simonsen & Robertson, 2013). It is grounded in ethics, respecting the rights of people to have a say in shaping the worlds in which they work (Robertson & Wagner, 2013, p. 65).

In the research study, three participatory design events were held with process, layout, and training design foci. One of the major outcomes focused on here is a change in the over-arching organizing principles for how people relate to the process and layout, referred to as the working design strategy in this paper. In the prior design, the organizing principle was for assembly components to be divided between the builders and the picking and assembling tasks shared between the builders. In the new design, the organizing principle is for the tasks to be divided between the builders (specialization in picking or assembling) and the components shared between the builders. This research compares the complexity of these two working designs in the operational domain of the assemble-to-order system.

A comparison of complexity is useful in terms of relative impact, but since it is a unit-less value it needs to be related to the broader system of value in the manufacturing system for it to have admissible meaning within the system. In the socio-technical systems literature, the aim of manufacturing is stated as: “to be economically productive” (Emery, 1989, p. 15). Most generally, this relates to turning inputs into outputs via a process. A widely used metric for this in an assembly system is cycle time; this research relates cycle time to assembly system operational complexity. Additionally, to test if cycle time has been improved by a working design in an assemble-to-order system is a challenge; direct comparisons between before versus after conditions may not be possible or practical if the product variety is high, which means that an analytical framework to create comparisons is needed.

The intent of the research presented here is to characterize relationships between people and assembly system complexity in design and operation as follows, (1) by defining an investigative process to analyze and compare (before versus after) working designs in an assemble-to-order system in the operational domain; and (2) by utilizing this analytical framework to assess the before versus after working designs arising out of a participatory design intervention case study.

2 Methodology

2.1 Case Study and Participatory Design

Since the research aims examine the operational domain, a case study research method is needed in order to understand the relationships between people and assembly system complexity in situ. This is
precisely one of the advantages of case studies - to “better understand phenomena embedded in situations through complex relationships” (Harling, 2012, p. 6). For this research, a manual, assemble-to-order system case study is studied with an industrial partner. In 2012, 396 different final products were assembled. The product variety is continuously expanding and the same final product may not be assembled twice. Two builders, builder A and builder B, assemble the final products with rigid and flexible components using a fixed product layout. The builder position is assigned on a temporary basis to temporary, part-time, or full-time employees. Builders are invited to be participants in this study, as they meet the inclusion criterion: a person who works directly or indirectly with the assembly process. The roles of supervisor, manager, lead hand, and planner also meet this criterion. For over a year, this case study has been studied with multiple methods that extend beyond this paper with a total of 32 participants, involving research ethics planning and review to ensure respect, safety, and fairness with participants (Townsend, Boulos, & Urbanic, 2014).

The participatory design (PD) events were designed with three design foci (process, layout, and training) – three themes that emerged from the pre-interview problem analysis (Townsend & Urbanic, 2014); specific pre-interview codes were included as motivations in the PD event design. The events took place in the production area and in a meeting room. The event outlines included questions such as, “how do you want to select the components each time that you build an assembly?” Participants engaged in answering the questions through discussion and by creating hands-on experiments to test out design ideas with assembly materials and simple supplies (paper, tape, Velcro, etc.). The event outline utilized the plan-do-check-act cycle (Deming, 2000) to facilitate mutual learning.

2.2 The Investigative Process

There is an inherent analytical challenge when assessing a design intervention in an assemble-to-order system because the final products are by nature highly varied, unpredictable, and may not be repeated. Therefore, before and after observations are not directly comparable. Here, the investigative process takes this into account by first creating observation models then using them to predict theoretical direct comparisons. The investigative process is outlined in Table 1. Steps 1-9 relate to the observation calculations and steps 10-11 relate to the theoretical calculations before (B) and after (A) the design intervention. Steps 1-9 are outlined in Figure 1 with steps 10-11 highlighted. Step 12 relates the observation and theoretical calculations.

| Step # | Investigative Process Step Description | Section |
|--------|----------------------------------------|---------|
| B 1 A 6 | Observe the assembly process. Gather data on the assembly product structure, layout, process steps, production phase, and cycle time. | 3.1 |
| B 2 A 7 | Test for elementary units in the data that explain variation in the cycle time population using ANOVA (Welch’s) and regression. | 3.1 |
| B 3 A 8 | Define complexity variables from the relevant elementary units and combine these variables into a complexity ratio (r). Calculate the complexity ratio (r) and mean cycle time (X-barCT) for each assembly code. | 3.2 |
| B 4 A 9 | Plot X-barCT vs. r, and then test the correlation with regression. | 3.3 |
| B 5 A 5 | Design intervention (participatory design), repeat steps 1-4 for the after (A) observations. | 3.4 |
| B 10 A 10 | Calculate theoretical complexity ratios, before (rTA) and after (rTB), for each assembly code per Figure 1. | 3.4 |
| B 11 A 11 | Using rTB and rTA and the appropriate correlation function (from step 4 or 9, Y=), calculate the theoretical mean cycle time (X-bar(CT,T)) | 3.4 |
| B 12 A 12 | Perform a mean cycle time comparison (before, after) using a paired t-test. | 3.4 |

**Table 1:** The investigative process (B-before, A-after)
3 Results and Analysis

3.1 Observation Data and Elementary Units

The observations are taken before (pre-observation) and after (post-observation) the design intervention. Within these phases, the samples are collected at random time intervals. A sample corresponds to one assembly cycle, one cycle time. Random sampling ensures that each cycle time elementary unit has an equal chance of being selected. Replacement amongst elementary units takes place, meaning the same combination of elementary units (assembly code, product family, total number of components, number of different components, etc.) can be sampled more than once. This occurs when several observations for a particular production run are gathered. These techniques add robustness to the data collection and subsequent statistical analysis through representativeness and independence amongst sample units. In the pre-observation (before), 226 data samples are analyzed (i.e. 226 assembly cycles) from 10 production runs. In the post-observation (after), 145 data samples are analyzed (i.e. 145 assembly cycles) from 8 production runs.

An exploratory statistical approach is used to detect if the elementary units in the observed data correlate with variation in the cycle time population. The following elementary units are tested. The total number of components (TT) is count data that refers to the number of components in an assembly. The number of assembly tasks (AT) is count data that refers to combining and positioning the selected assembly components. The number of picking tasks (PT) is count data that refers to selecting the components. The assembly code is categorical data that refers to an assembly type
identifier. The pallet count is discrete data that refers to the number of finished assemblies that will fit on one pallet (relative size of the finished assembly). The production phase is categorical data that refers to when the observations are taken relative to the start, end, or a full production run. The product family is categorical data that refers to a common assembly platform. The number of different components (DT) is count data that refers to the number of distinct component types in an assembly.

Since the elementary unit groups involve either categorical, discrete, or count data, ANOVA (Analysis of Variance) tests are conducted. For count data that has a range over 10, a regression analysis is also conducted (3M Canada, 2005, p. 38). The null hypothesis (Ho) tests if the means of the groups for a particular elementary unit are statistically equal. The Ho is rejected when the p-value is < α, where α=0.05 for a 95% degree of confidence. For a normality best fit, cycle time transformations can be performed (ReVelle, 2001, p. 329). Here, cycle time data is multiplied by a factor of 1/(archived minimum mean cycle time) for confidentiality then transformed for normality with a Box-Cox transformation (pre-observation) and log-logistic transformation (post-observation); the normal probability plots are tested with a fat pencil test. In addition, groups in the ANOVA are tested where the sample size of each group (n) is > 15 to further build robustness around normality (Minitab, 2015, p. 10). In case of unequal variances in the response data, Welch’s ANOVA is used. After the Welch’s ANOVA is conducted, the normal probability plot of the residuals is inspected with a fat pencil test. The elementary units, their groups, and the number of samples in each group (n) are outlined in Table 2; the associated Welch’s ANOVA results are presented in Figure 2.

| Elementary units | Pre-observation (Before) | Post-observation (After) |
|------------------|--------------------------|--------------------------|
| TT               | 30(n=20), 31(n=16), 33(n=28), 36(n=28), 41(n=28), 42(n=56), 66(n=20) | 28(n=20), 32(n=19), 34(n=23), 49(n=23), 52(n=18), 69(n=22) |
| AT, PT           | 10(n=16), 11(n=76), 12(n=56), 16(n=48) | 9(n=20), 11(n=19), 13(n=23), 14(n=41), 21(n=22) |
| Assembly code    | 3(n=16), 4(n=28), 6(n=28), 7(n=20), 8(n=20), 9(n=56), 10(n=28) | 11(n=20), 12(n=18), 14(n=19), 15(n=23), 16(n=22), 17(n=23) |
| Pallet count     | 12(n=180), 20(n=20), 25(n=26) | 12(n=83), 20(n=39), 25(n=23) |
| Production phase | end(n=160), full(n=40), start(n=26) | full(n=46), start(n=99) |
| Product family   | a(n=20), b(n=84), c(n=96), d(n=26) | a(n=39), b(n=23), c(n=34), d(n=23), e(n=26) |
| DT               | 3(n=76), 5(n=36), 6(n=28), 7(n=20), 9(n=56) | 5(n=68), 6(n=30), 7(n=28), 9(n=19) |

Table 2: Elementary unit groups and sample size (n)

| Elementary Unit | Before or After | F-value | P-value | ANOVA (Welch’s) |
|-----------------|----------------|---------|---------|-----------------|
| TT              | Before         | 12.41   | 0.00    | 30.49%          |
|                 | After          | 30.32   | 0.00    | 50.99%          |
| AT, PT          | Before         | 14.41   | 0.00    | 18.58%          |
|                 | After          | 25.97   | 0.00    | 46.24%          |
| Assembly code   | Before         | 12.41   | 0.00    | 30.49%          |
|                 | After          | 30.32   | 0.00    | 50.99%          |
| Pallet count    | Before         | 20.55   | 0.00    | 19.51%          |
|                 | After          | 20.16*  | 0.13*   | *Note: P-value is > α |
| Production phase| Before         | 75.29   | 0.00    | 19.19%          |
|                 | After          | 103.91* | 0.00    | 41.75%          |
| Product family  | Before         | 14.46   | 0.00    | 20.33%          |
|                 | After          | 34.74   | 0.00    | 32.70%          |
| DT              | Before         | 13.56   | 0.00    | 23.34%          |
|                 | After          | 17.34   | 0.00    | 28.00%          |

Figure 2: Welch’s ANOVA results, testing correlation between elementary units and cycle time
For all but one test in Figure 2, the p-value is 0.00 and Ho is rejected (p<0.05); the mean cycle times between groups in the elementary unit are not the same. Thus, the variation in elementary unit grouping is significant in terms of explaining the variation in cycle time. The degree to which the elementary unit groups account for cycle time variation is expressed by R-sq; the R-sq values generally increase from before to after (Figure 2). The next step is to further characterize these relevant elementary units into complexity variables in a model that further explains cycle time variation relative to the working designs (Section 3.2). Another explanation for the increase in R-sq is that additional elementary units, affecting the before design in particular, exist; though this paper focuses on the elementary units stated, the proposed approach can be used to test for additional elementary units. Additionally, there is likely to be system noise that is difficult to make explicit into an elementary unit. This interpretation may be supported by the F-values, which express a signal-to-noise ratio; the general trend in Figure 2 is that the F-values increase from before to after, with more system noise before versus after. It’s important to note that the high F-value for production phase (after) is likely due to only two groups being compared (full and start). Production phase (after) is included in the Welch’s ANOVA in Figure 2 for comparison, but it can more aptly be analyzed in a two sample t-test wherein a T-value versus F-value is calculated (T-value=10.19, p-value=0.00).

The one exception in the results (*), where the p-value is > 0.05, is for the pallet count (after). For the pallet count elementary unit, the p-value=0.00 before but the p-value=0.13 after; the before result rejects the null hypothesis while the after result accepts it. In other words, the pallet count contributes to variation in the cycle time population before but not after the design intervention; this means that pallet count may or may not be significant to understanding variation in cycle time. To compare before and after states of the assembly system in the subsequent investigative steps, it is important to include pallet count in this case because it is significant in the before cycle time population.

For count data where the range is > 10, a linear regression analysis is also conducted. This condition only applies for TT (before), TT (after), and AT (after). The linear regression analysis is conducted with a 95% degree of confidence, and the normal probability plots and residuals are checked for normality with a fat pencil test. For TT (before), the count range is 66-30=36; the regression result is p-value=0.54, R-Sq=0.2%. For TT (after), the count range is 69-28=41; the regression result is p-value=0.00, R-sq=20.4%. For AT (after), the count range is 21-9=12; the regression result is p-value=0.00, R-sq=33.0%. These results show that in the observation data, there is not a linear correlation present for TT before (0.54 > 0.05) but there is a linear correlation present for TT after (0.00 < 0.05) and AT after (0.00 < 0.05). The next steps in the investigative process inquire into reasons for this – to relate the working designs to complexity and cycle time.

### 3.2 Complexity Variables From Elementary Units

This section begins by defining a complexity variable for each elementary unit: production phase (V), pallet count (PC), number of components (TT), number of different components (DT), number of picking tasks (PT), and number of assembling tasks (AT). These variables are grouped into a complexity ratio (r) for each assembly code (final product type) with a corresponding mean cycle time (X-bar[T]). These data points (r, X-bar[T]) are then plotted and analyzed with linear regression for comparative analysis. In total, 18 different production runs of unique assembly codes (i) are observed.

The observations relate to a production phase (V) in terms of the number of observations taken in the production run (n), and the position of the observations relative to the beginning (Equation 1) or end (Equation 2) of a production run. A full production run corresponds to Equation 2, versus Equation 1, based on the ANOVA analysis in Figure 2 (before), where the mean cycle time difference between end and full (0.23min/assembly) is less than the difference between beginning and full (0.61min/assembly). This suggests that the typical curve between production phase beginning and end may have a longer end tail, which is also why 0.5 is not a suitable V value for a full observation position (because 0.5 would assume a linear relationship). The exact curve cannot be drawn from the ANOVA, since this involves categorical data, but what is known is that the poles (beginning and end)
are critical; accordingly, the beginning and end of the production run spectrum are emphasized as datum references in Equations 1 and 2 respectively, which correspond to complexity values of 1 and 0.

\[ V_i = 1 - \left( \frac{n_i}{2Vol_{max}} \right) \]  
\[ V_i = \frac{n_i}{2Vol_{max}} \]  

In Equations (1) and (2), \( i \) represents a given production run, where in this case \( i = 1, 2, \ldots, 10 \) before the design intervention and \( i = 11, 12, \ldots, 18 \) after; \( n_i \) represents the number of observation samples in \( i \) (i.e. number of assembly cycles, or number of final assemblies built, observed in the production run), where \( n_i/2 \) represents the midpoint of the observations; and \( Vol_{max} \) represents the maximum total number of final assemblies required to complete the order (i.e. production run volume) across all \( i \) (i.e. a theoretical observation maximum, or datum), which is 200 in this case.

The pallet count variable, PC, is calculated based on the ANOVA analysis (Figure 2) for the pallet count elementary unit. A relative ratio is based on mean cycle time \( (X\text{bar}_{j,k}) \), where \( j \) is the pallet count (or number of finished assemblies that will fit on one pallet, \( j = 12, 20, 25 \)) and \( k \) = before or after the design intervention. This is outlined in Equation 3 with results in Table 3.

\[ PC_{j,k} = \frac{X\text{bar}_{j,k}}{\sum_{j=12,20,25} X\text{bar}_{j,k}} \]  

| Before or after (k) | Pallet count (j) | Xbar\(_{j,k}\) | \( \sum_{j=12,20,25} X\text{bar}_{j,k} \) | PC\(_{j,k}\) |
|---------------------|-----------------|--------------|---------------------------------|----------|
| Before              | 12              | 3.67         | 10.77                           | 0.34     |
|                     | 20              | 2.76         | 10.77                           | 0.26     |
|                     | 25              | 4.34         | 10.77                           | 0.40     |
| After               | 12              | 2.16         | 6.31                            | 0.34     |
|                     | 20              | 1.87         | 6.31                            | 0.30     |
|                     | 25              | 2.28         | 6.31                            | 0.36     |

**Table 3:** Calculating the values for the pallet count, PC, variable

The remaining elementary units from Figure 2 are correlated more specifically with the working design strategy (before and after) as follows. Each production run \( (i) \) relates to a particular assembly (or final product) code, which corresponds to a product family and dictates TT, DT, PT, and AT. How these factors \( (F) \) are divided between the two assembly builders, builder A and builder B, is determined by the process and layout design (working design strategy). TA and TB refer to the number of total components that builders A and B handle. DA and DB refer to the number of different components that builders A and B handle. PA and PB refer to the number of picking tasks that builders A and B perform. AA and AB refer to the number of assembly tasks that builders A and B perform. The degree of balance of the factors \( (F) \) between builders A and B can be explained by the ratio of the distribution \( (A-B) \) over the total \( (T) \), Equation 4.

\[ FR_i = \frac{FA_i - FB_i}{FT_i} \]  

Equation 4 is used to calculate TR, DR, PR, and AR, where \( F = T,D,P, \) and \( A \). The variables are then combined into a complexity ratio \( (r) \), Equation 5, with corresponding observed mean cycle times for the assembly code \( (X\text{-bar}_{CT}) \), in minutes/assembly) summarized in Table 4.

\[ r_i = V_i + PC_i + |DR_i| + |TR_i| + |PR_i| + AR_i \]  

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3.3 Comparing Before vs. After Designs: Testing Correlation Between Cycle Time and the Complexity Ratio

From Table 4, the points \((r, X_{\text{bar,CT}})\) are plotted as two series - before and after (the design intervention) in Figure 3. The correlation between mean cycle time and the complexity ratio is tested with linear regression, which is performed with a 95% degree of confidence. The normality of the mean cycle times is confirmed with a probability plot and fat pencil test.

![Figure 3: Mean cycle time vs. complexity ratio (before and after)](image-url)
As shown in Figure 3, it is possible to consider the picking and assembling ratios, PR and AR, separately or together in terms of the complexity ratio. In the prior design, considering them separately yielded a higher R-sq value (0.81) than together (0.75). In the post-design, there is only a significant correlation when PR and AR are considered together. This aligns with the design strategies in place. In the prior design, the picking and assembling tasks are shared between the builders, so the aim is for the tasks to be equal between individuals. In the new design, the tasks are divided between the builders (picking or assembling), so the aim is for the tasks to be offset between individuals.

From Figure 3, it is clear that the new design (after) is organizing complexity with greater efficiency than the prior design (before) – for any given value of complexity, the mean cycle time is lower with respect to the new design (after) versus the prior design (before). The following question, however, arises: does the new system design yield a higher complexity value for a given assembly (final product) compared to the prior system design? With an assemble-to-order system with high final product variety, it is extremely challenging to create a direct observation comparison of this kind.

While a direct observation comparison is not viable, it is possible to use the models generated from the observation data to predict a mean cycle time using the plotted lines in Figure 3 with a complexity ratio. It’s possible to determine the complexity ratio theoretically by analyzing the raw data (e.g. product information) with the alternative (before or after) working design strategy. In doing so, a direct pairwise comparison can be made between the same final product in the same observation conditions relative to the before and after design theories. From this direct comparison, it’s possible to determine if the new design improves cycle time concurrently with complexity organization.

### 3.4 Comparing Before vs. After Designs: Testing Pairwise Comparison

To calculate a theoretical complexity ratio \( r_f \) of the assembly system before and after a design intervention, the investigative process outlined in Section 2.2 is applied, specifically step 10 in Table 1. This approach is further detailed in a matrix, Figure 4 (with the same shading as Figure 1), outlining the complexity variables with system conditions for observation and theoretical calculations.

| Before Working Design Strategy \( \gamma_B = \) | Before Observation | After Theoretical Before | After Observation | After Theoretical After |
|----------------------------------------------|--------------------|------------------------|--------------------|------------------------|
| Product Structure, Pallet Count, & Production Phase \( \text{DT, TT, PT, AT, PC, & V} \) | \{TA, TB, DA, DB, PA, PB, AA, AB \} \( \rightarrow \) \( X-bar_{CT} \rightarrow (r_{TA}, X-bar_{CT,TA}) \) | \{TA, TB, DA, DB, PA, PB, AA, AB \} \( \rightarrow \) \( X-bar_{CT} \rightarrow (r_{TB}, X-bar_{CT,TB}) \) | \{TA, TB, DA, DB, PA, PB, AA, AB \} \( \rightarrow \) \( X-bar_{CT} \rightarrow (r_{TA}, X-bar_{CT,TA}) \) | \{TA, TB, DA, DB, PA, PB, AA, AB \} \( \rightarrow \) \( X-bar_{CT} \rightarrow (r_{TB}, X-bar_{CT,TB}) \) |

**Figure 4:** Complexity variables for theoretical and observation calculations, before and after

As shown in Figure 4, the values of the complexity variables related to the product structure totals (DT, TT, PT, AT), pallet count (PC), and production phase (V) are held constant with the observation alternative. With this data, the distribution of work between builder A and B (TA, TB, DA, DB, PA, PB, AA, AB) is calculated using the contrasting working design strategy, which consequently creates new corresponding ratios (TR, DR, PR, AR). With these complexity variables, the theoretical complexity ratio \( r_f \) is calculated. Using \( r_f \) and \( Y^* \) (the correlation between mean cycle time and the complexity ratio for the given working design strategy, Figure 3), the theoretical mean cycle time \( x-bar_{CT,TA} \) is calculated. These results for each assembly code \( i \) are shown in Table 5.
| Before/ After | Assembly Code (i) | \( V_i \) | \( PC_i \) | \( TR_i \) | \( DR_i \) | \( PR_i \) | \( AR_i \) | \( r_{iT} \) | \( X-bar_{CTL,T} \) |
|--------------|------------------|---------|---------|---------|---------|---------|---------|---------|-----------------|
| After        | 1                | 0.03    | 0.34    | -0.07   | -0.20   | 0.50    | -1.00   | 1.13    | 1.02            |
|              | 2                | 0.03    | 0.40    | -0.09   | -0.40   | 0.27    | -1.00   | 1.65    | 1.78            |
|              | 3                | 0.96    | 0.40    | -0.13   | -0.40   | 0.20    | -1.00   | 2.69    | 3.33            |
|              | 4                | 0.07    | 0.34    | -0.27   | -0.67   | -0.38   | -1.00   | 2.72    | 3.38            |
|              | 5                | 0.98    | 0.34    | -0.08   | -0.40   | 0.33    | -1.00   | 2.46    | 2.99            |
|              | 6                | 0.07    | 0.34    | -0.17   | -0.67   | -0.09   | -1.00   | 2.33    | 2.80            |
|              | 7                | 0.05    | 0.34    | -0.09   | -0.67   | 0.25    | -1.00   | 1.90    | 2.16            |
|              | 8                | 0.05    | 0.26    | -0.20   | -0.43   | -0.09   | -1.00   | 2.03    | 2.35            |
|              | 9                | 0.14    | 0.34    | -0.12   | -0.33   | 0.08    | -0.08   | 0.93    | 0.72            |
|              | 10               | 0.07    | 0.34    | -0.15   | -0.50   | 0.00    | -0.91   | 1.97    | 2.27            |
| Before       | 11               | 0.05    | 0.30    | 0.71    | 0.14    | 0.11    | 0.11    | 1.42    | 2.76            |
|              | 12               | 0.05    | 0.34    | -0.12   | 0.00    | -0.29   | -0.29   | 1.07    | 2.33            |
|              | 13               | 0.02    | 0.34    | 0.00    | -0.14   | -0.33   | -0.33   | 1.17    | 2.45            |
|              | 14               | 0.95    | 0.30    | 0.13    | -0.33   | -0.27   | -0.27   | 2.25    | 3.76            |
|              | 15               | 0.94    | 0.34    | 0.00    | 0.20    | 0.00    | 0.00    | 1.48    | 2.83            |
|              | 16               | 0.95    | 0.34    | -0.01   | 0.20    | 0.33    | 0.33    | 2.17    | 3.65            |
|              | 17               | 0.94    | 0.36    | 0.22    | -0.20   | -0.08   | -0.08   | 1.88    | 3.31            |
|              | 18               | 0.97    | 0.34    | -0.20   | 0.00    | -0.54   | -0.54   | 2.59    | 4.16            |

Table 5: Theoretical complexity variable values and associated mean cycle time

From Table 5 and Table 4, mean cycle time pairs (before, after) are created for direct comparison: \( (X-bar_{CTL,B}, X-bar_{CTL,T}) \), \( n=10 \) and \( (X-bar_{CTL,B}, X-bar_{CTL,A}) \), \( n=8 \). With a paired t-test (95% degree of confidence), the effect of the design intervention on mean cycle time is tested. Ho states that the difference between the after mean cycle time and the before mean cycle time is 0. The alternative is that the difference does not equal 0. The after-before difference is plotted on a probability plot and checked with a fat pencil test to confirm normality; results are shared in Table 6 and Figure 5.

|             | n   | Mean  | Standard Deviation | Mean Standard Error |
|-------------|-----|-------|--------------------|---------------------|
| After Mean Cycle Time | 18  | 2.34  | 0.90               | 0.21                |
| Before Mean Cycle Time | 18  | 3.05  | 0.73               | 0.17                |
| Difference   | 18  | -0.72 | 0.64               | 0.15                |

Table 6: Paired t-test results, 95% confidence, after – before mean cycle time

Figure 5: Paired t-test histogram of differences, after - before mean cycle time
From the paired t-test analysis, the T-value is -4.78 with a corresponding p-value of 0.00. Since p<α (where α=0.05 for a 95% degree of confidence), the null hypothesis is rejected and it can be concluded that there is a statistically significant mean difference in mean cycle time before and after the design intervention. The mean cycle time is lower after the design intervention (2.34 ± 0.90 minutes/assembly) than before the design intervention (3.05 ± 0.73 minutes/assembly), with a statistically significant mean difference of -0.72 (95% confidence interval, -1.04 to -0.40) minutes/assembly. In other words, the mean cycle time was reduced by 0.72 minutes/assembly by the participatory design intervention, specifically by the after working design strategy outcome of the participatory design events when compared to the before working design strategy.

4 Conclusion

This research develops an investigative process whereby a participatory design intervention in an assemble-to-order system is assessed with a complexity analysis to ultimately understand cycle time impact. From observation data (n=226 before, n=145 after), the relationships between elementary units and the cycle time population are tested with Welch’s ANOVA and regression analysis. The elementary units are then translated into a complexity ratio via complexity variables to relate the working design strategy to the mean cycle times. The correlation between the complexity ratio and mean cycle time is tested with regression analysis (95% degree of confidence); R-sq=0.75 and 0.81 (before working design) and R-sq=0.88 (after working design). The regression plot illustrates that the after working design strategy organizes the complexity ratio (r) more efficiently compared to the after working design strategy by virtue of its lower line placement on the mean cycle time versus complexity ratio plot (Figure 3). These correlations also serve as a model to predict theoretical values for mean cycle time direct comparison. The before and after mean cycle times for theoretical and observation values are compared with a paired t-test; the mean cycle time is found to be lower after the design intervention versus before with a statistically significant mean difference (after – before) of -0.72 minutes/assembly. By virtue of these results, the proposed investigative process proves successful in analyzing and comparing two working designs in an assemble-to-order system in the operational domain, which are positioned before and after a participatory design intervention. This participatory design approach and investigative process contribute to the literature in further characterizing the relationships between people and assemble-to-order system complexity.

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