IDENTIFYING AND COMPARING SUBPROBLEMS IN FACTORY DESIGN PROCESSES

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ABSTRACT

When a design team faces the problem of designing a complex system, they are required to make several decisions. Because such design problems are difficult to solve all at once, teams often decompose the design problem into several smaller subproblems. This paper discusses the results of a study designed to understand how design teams decompose a factory redesign problem into sets of related subproblems and compare the subproblems obtained for each design team. This exploratory study analyzed the design activities of eight teams of professionals and used clustering to group the variables that the design teams considered. We found that the design teams used different decomposition strategies and different subproblems, but they more often considered subproblems with design variables of the same type, and some teams followed a top-down design process.

Keywords: Human behaviour in design, Collaborative design, Design process, Decomposition

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1 INTRODUCTION

Designing a system is a complex activity. Design teams who are solving design problems must make decisions about the many design variables. Because many design problems cannot be solved all at once, design teams divide the complex problem into smaller, less complex subproblems that decouple the design decisions. Thus, the reasoning and techniques used to decompose the complex design problem into subproblems and the composition of the subproblems may affect the quality of the solutions that are developed. Therefore, it is imperative to understand how design engineers decompose problems. Ultimately, identifying the sets of subproblems that lead to better quality designs could be helpful for design engineers and will also enable future research on design cognition and design guidelines and methods.

To increase our understanding of decision decision-making and decomposition, we have pursued a series of studies in which we observed teams engaged in design problems and analyzed their design processes. A key feature of our approach is that we assume that the team decomposes the design problem into subproblems and that the variables that a team discusses concurrently are likely to belong to the same subproblem. The key research question is the following: *How do design teams decompose design problems*?

The research study described in this paper analyzed decompositions across eight teams including the variables in the subproblems and the similarities and differences of subproblems across teams. This exploratory research examined how design teams tackle a system design problem, identified the subproblems that they solved, and documented their similarities and differences through multiple types of analysis. This study thus complements similar studies that observed individual designers (Liikkanen and Perttula, 2009; Ho, 2001; Gero and Mc Neill, 1998; Guindon, 1990).

The remainder of the paper is organized as follows: Section 2 discusses the related literature; Section 3 describes the data collection procedures. Section 4 presents the data analysis techniques. Section 5 compares the results for the eight teams. Section 6 discusses these results, and Section 7 concludes the paper.

2 REVIEW OF RELATED WORK

Decision making in the engineering design process is an iterative process of generating, evaluating, and selecting design alternatives (Ullman, 2001; Renzi et al., 2017). Decision making strategies discussed in the literature for solving system design problems include three categories: decision-making problem solving, problem structuring method, and multi-criteria decision-making (Renzi et al., 2017). Empirical studies of design decision-making have considered the decision-making process in parametric design (Lee and Ostwald, 2020) and how designers make decisions with several types of information and limited resources (Chaudhari et al., 2020).

Decomposing a design problem is especially crucial when a design team solves problems as opposed to a single designer. Understanding how design teams decompose complex problems gives insight into the improvement of design quality (Liikkanen and Perttula, 2009; Ho, 2001). Decomposition in design problems can be of two kinds, implicit and explicit decomposition (Morency, 2017; Liikkanen and Perttula, 2009; Ho, 2001). The analysis of three electronic design episodes using macro strategies showed decomposition happened at early stages of design process following top-down and bottom-up approaches (Gero and Mc Neill, 1998). A study of engineering design teams (Milovanovic et al., 2021) considered how each team combined solutions to subproblems at the different levels in a hierarchical decomposition of the design problem. They found that teams moved between problems at different levels throughout the design process, but that study did not identify each team's specific subproblems.

In our research, decomposition refers to dividing the design problem into smaller subproblems that have have fewer design variables (Tobias et al., 2016; Gralla and Herrmann, 2014). Identifying which design variables are in which subproblems can be a challenge, however (Morency et al., 2017). Previous work done on this research involved studying medical POD design teams and evaluating the performance of multiple clustering algorithms (Morency, 2017). Our previous work described our overall research approach and experiments to identify the subproblems that were used by design teams using different clustering techniques (Morency et al., 2017; Tobias et al., 2016; Gralla and Herrmann, 2014; Morency, 2017) but did not compare the subproblems across teams. The current study builds on this work, but this study uses a new technique to identify subproblems (from complete and partial timelines) and compares the subproblems that the different teams considered.

3 DATA COLLECTION

In three separate sessions, we collected data from eight teams who solved a factory redesign problem. For more details about the problem and data collection, see Morency et al. (2017); Tobias et al. (2016); Gralla and Herrmann (2014).

This research considered discussions of eight teams (labeled Teams F, H, J, K, L, X, Y, and Z) of professionals with expertise in manufacturing. These teams were given the task of redesigning a factory layout as a part of a two-day lean facility design course. Each team had four or five persons. The participants had an average industry experience of 17 years and were grouped by experience level to ensure each team had a good mix of more experienced persons and less experienced persons. The exercise took about four hours.

The design teams were given a fictional design of a manufacturing facility called We Assemble Super Terrific Equipment (WASTE) Inc. and a problem statement aimed at redesigning of the WASTE Inc. facility based on a set of factory redesign goals and design constraints. The goal of the discussion was to improve upon the existing design which had trouble meeting delivery targets. Each team discussed the problem at length, and a video camera recorded the team's discussions. The video camera captured the layout that the team was creating on a diagram spread on a large table. The audio recording of their discussion was used in combination with the visual information to understand their design decisions and subproblems.

4 DATA ANALYSIS

We used the data analysis procedures to explore the teams' discussions and understand how they decomposed the design problem. Our analysis combined qualitative and quantitative techniques to identify subproblems and create timelines that describe when teams discussed their subproblems.

4.1 Coding team discussions

We coded the teams' discussions to understand how teams decomposed the problem into subproblems. The first step was to identify the variables that the teams discussed using techniques based on grounded theory (Glaser and Strauss, 2017; Corbin and Strauss, 2014) and process mapping (Langley, 1999).

We watched the videos of each design team's design sessions and recorded all the variables they discussed in each 2-minute time segment. By iteratively comparing similarly coded segments to each other and to the working definitions of the codes, we refined the set of codes and definitions to develop a codebook that listed all the variables that any team discussed with precise definitions. (Videos were recoded according to the final codes.) Many of the variables were related to the location, size, staffing, and internal layout of the functional areas in the factory (e.g. frame fabrication, paint, or machine assembly). A total of 82 variables were identified.

4.2 Clustering variables into subproblems

We then used spectral clustering to identify the subproblems by grouping the variables that were discussed during the same time interval. The effectiveness of the spectral clustering in grouping meaningful clusters has been shown in previous research (Sarkar et al., 2009, 2014; Morency et al., 2017).

Spectral clustering makes use of eigenvalue spectrum of the data to perform dimensionality reduction before clustering in this reduced dimension space (Sarkar et al., 2014). The first step in the process was

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to calculate the relative count for each pair of variables and create the relative count matrix A. We will use the following notation:
$n(i)$: number of time segments in which variable i was discussed
$n(i,j)$: number of time segments in which both variable i and variable j were discussed
$a(i,j)$: the relative count, an element of A ($a(i,i) = 0$).

$$a(i,j) = n(i,j)/(n(i) + n(j) - n(i,j))$$

If $a(i,j) = 0$ for all j, then variable i was removed from consideration because it was not concurrent with any other variables. Let r be the number of variables remaining. Next, we determined the eigenvectors and eigenvalue spectrum for A, which yielded two additional matrices, D and V. D is the r x r diagonal matrix of the eigenvalues. V is the r x r matrix of eigenvectors. After conducting a sensitivity analysis that showed that using more eigenvalues did not significantly change the results, we decided to use the six largest eigenvalues to generate the reduced-dimension points. We created a matrix U that contained the eigenvectors for the largest eigenvalues and a diagonal matrix S containing the corresponding eigenvalues. Then, the product UxS is a set of points in a six-dimensional space, and each point corresponds to one variable. We clustered the points by calculating the Euclidean distances between every pair of points in this reduced-dimension space and using the MATLAB function linkage to generate a hierarchical binary cluster tree, which can be visualized as a dendrogram.

To select the clusters from the dendrogram, we used a procedure that systematically combined variables into clusters with a sufficiently large cluster "strength," which is the average relative count of the pairs of variables in a cluster. (This can also be viewed as a measure of the similarity of the variables in a cluster.) This metric is different from the pair-wise distance that was used in spectral clustering. The procedure combined individual variables into clusters one at a time (or combined two clusters). We used a threshold of 0.3; if adding a variable to a cluster reduced the cluster strength below this level, then the procedure stopped adding variables to the cluster.

Although the clusters describe which variables were discussed with others across the entire design process, teams sometimes discussed some sets of variables for a shorter time, which might prevent such a set of variables from being identified as a cluster, especially if some of the variables were also discussed with other variables during a different part of the design process. Therefore, we also analyzed shorter time intervals to capture more details about how the teams designed the factory. We repeated the clustering approach on subtimelines that were only part of the entire design process. We divided the timeline into multiple equal-sized subtimelines. The number of subtimelines ranged from two to six. After creating clusters for each subtimeline, we used an iterative process to combine these clusters into "groups" of variables. Initially, each cluster was a group by itself. The search considered all pairs of clusters; if one cluster were a subset of another cluster, then their groups were combined. Because a variable can be in multiple clusters (from different subtimelines), a variable can end up in multiple groups. The number of groups per team ranged from 9 to 20, and the number of variables per group ranged from 2 to 18. We treated each group as one of the subproblems that the team considered.

We then systematically classified the subproblems to describe the focus of each subproblem. For example, one subproblem (Group 4, Team H) consisted of the variables "Location of gym" and "Size of gym." This subproblem focuses on *one area* of the factory – the gym – and determines *multiple attributes* of that area – its location and its size. In contrast, another subproblem (Group 14, Team F) consisted of the variables "Location of storage" and "Location of incoming material." This subproblem focuses on *one attribute* – location – of *multiple areas* of the factory. We labeled all the subproblems to describe their main focus in the following manner.

First, we identified all the potential focuses for the subproblems using a qualitative coding process: we examined every subproblem and labeled each one with its likely focus. In the examples above, this was straightforward, but some subproblems focused on a *set* of different areas that were related to one another in more subtle ways, such as forming an adjacent series of operations in the factory (such as module assembly), or relating to one function (such as storage) in multiple areas of the factory. The

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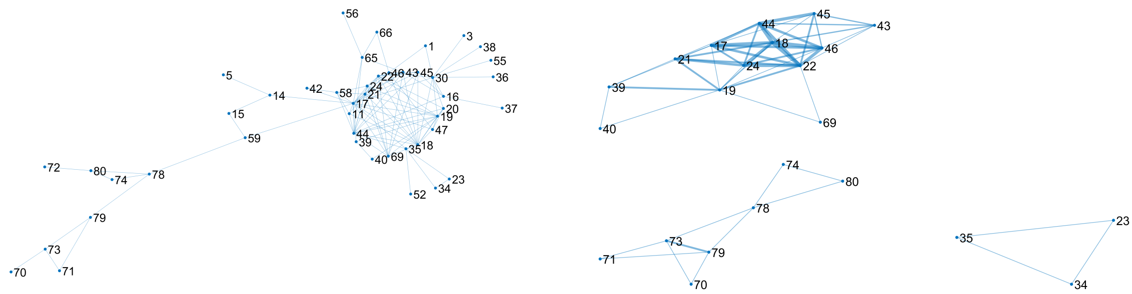
result was a set of attributes and a set of "area sets" (AS), listed in Figure 2, below. We then determined quantitatively which of these many possible labels best fit each subproblem. To do so, we examined each subproblem and calculated the percentage of the variables in that subproblem that were related to each potential focus (attribute or area set). If the focus with the highest percentage of variables was greater than 50%, this was identified as the subproblem's focus. These focus labels provide a qualitative description of each subproblem's function in the problem-solving process.

4.3 Common pairs

We also considered "common pairs," pairs of variables that are together in at least three subproblems across all eight teams. That is, variables i and j form a common pair if there are at least three subproblems that include both i and j. We identified 115 common pairs that involved 45 variables. Figure 1a shows these pairs. Note that the variable numbers indicate the type of variable: variables 11 to 15 were internal layout variables; variables 16 to 47 were location variables; variables 49 to 68 were size variables; and variables 70 to 82 were staffing variables. Thus, we can see that some staffing variables were in common pairs with other staffing variables and that some location variables were in common pairs with other location variables.

4.4 Triplets

We also considered "triplets," sets of three variables that were discussed (coded) in the same time segment. We identified the triplets for each team and found those that occurred in at least three teams. Of the 1,277 unique triplets across all eight teams, only 45 triplets occurred in at least three teams. Of these, eight occurred in exactly four teams, and three occurred in exactly five teams. Figure 1b is a graph that shows the variables in these triplets.



(a) Graph of variables that are in the common pairs. Each node represents a variable, and each edge corresponds to a common pair.

(b) Graph of triplets that occurred in at least three teams. Each node represents a variable, and edges connect variables in the same triplet.

Figure 1.

5 RESULTS

We identified 82 variables that the teams discussed and 127 subproblems. The largest subproblem had 18 variables. The number of subproblems per team ranged from 9 to 20.

This section presents a series of analyses for each team and then compares the results for the eight teams to investigate the research question discussed in Section 1.

5.1 Types of subproblems

Only a few subproblems focused on neither an attribute nor an area. Many subproblems focused on a single attribute or a single area (such as multiple attributes of the control box area or a single attribute, such as staffing, for multiple areas). No subproblems focused on a single attribute and a single area. This suggests that subproblems tend to be driven by one type of concern: either a particular area (or set of

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areas) in the factory, or the allocation of a particular scarce resource, such as staff or space on the factory floor.

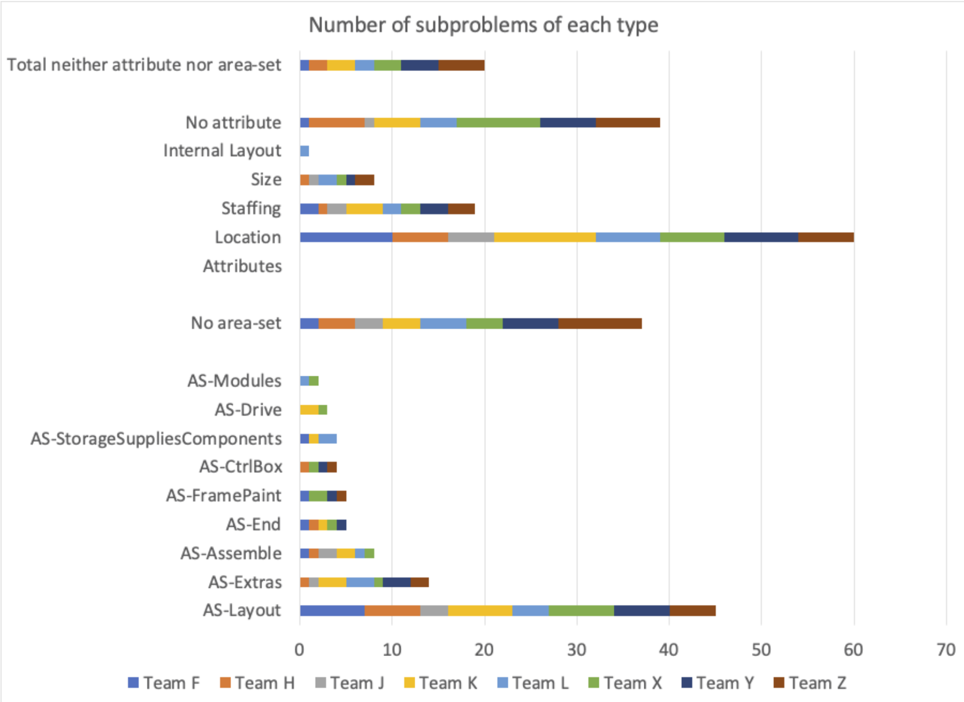
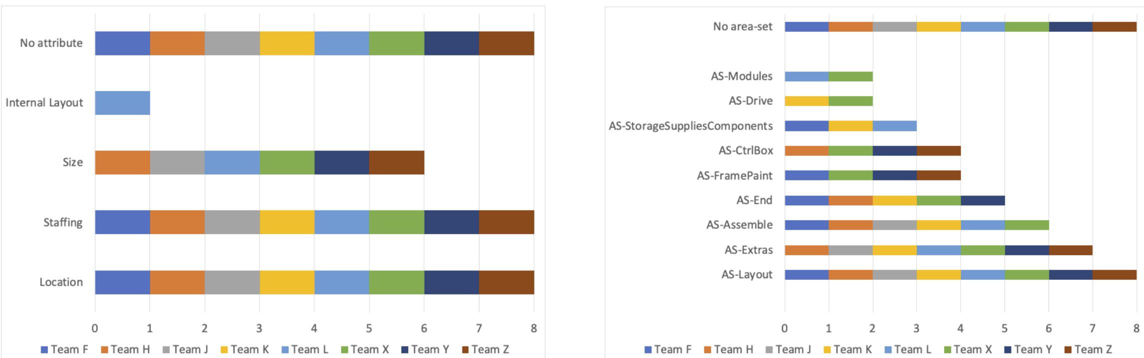


Figure 2. Number of subproblems for each team that focus on a single attribute or a single area.

As shown in Figure 2, many of the teams' subproblems focused on locating areas in the factory (location attribute and layout area-set), as expected, since this is the core goal of the challenge. Staffing was also a common grouping, likely because staffing resources make choices in different areas interdependent.

Another way to examine this question is to ask which types of subproblems were considered at least once by each team. This helps to focus on the similarities across teams rather than simply how many different subproblems each team employed. Figures 3a and 3b show the number of teams that considered at least one subproblem focused on each attribute and each area-set, respectively.



(a) Subproblems focused on each attribute.

(b) Subproblems focused on each area set.

Figure 3. Number of teams that studied (at least one) subproblem of various types.

All teams solved subproblems centered on the location and staffing of various areas, and most also solved subproblems related to the size of areas. This is reasonable because these decisions are interdependent across different areas of the factory.

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Regarding the area sets, all teams solved problems related to layout. Most of the teams also studied assembly. Assembly is one of the largest groups of related areas in the factory, and the processes are roughly sequential, so this grouping is useful. A smaller but still substantial number of teams grouped smaller sets of related functions: framing and painting, functions at the end of the process, and those related to the control box. These are all functions that happen sequentially, so it makes sense to treat them as subproblems.

The extras subproblem (which was also very common across teams) and a storage, supplies, and components subproblem are different from the others in that they do not group sequential functions. Instead, these are functions that must be spread throughout the process (and throughout the factory). They are related to one another only because their relationships to other functions are similar: either they are unrelated (extras) or they have a one-to-one relationship with individual factory areas (such as storage). It is interesting that so many teams considered these as subproblems.

5.2 Timing

Figure 4 shows the time segments in which each team discussed two or more variables from a staffing subproblem or a location subproblem. (The horizontal axis is a scaled time value, where time equals 0 at the first time segment in which the team discussed any variables, and time equals 1 at the last such time segment.) Some teams (Teams H, L, Y) discussed these staffing subproblems only once during design process. Other teams discussed these subproblems multiple times during the design process (Teams F, J, K, X, Z). No team discussed these subproblems regularly throughout the entire design process.

It appears that all of the teams discussed location subproblems, but the patterns varied across teams. Team H discussed location subproblems early but rarely after that; Team X had a similar pattern for their location subproblems. Team J discussed their location subproblems more during the last half of their design process. Teams F, J, K, Y, and Z discussed location subproblems throughout the process. The teams often discussed the subproblems that focused on staffing variables separately from the subproblems that focused on location variables. This suggests that the teams decoupled the staffing decisions from the layout decisions.

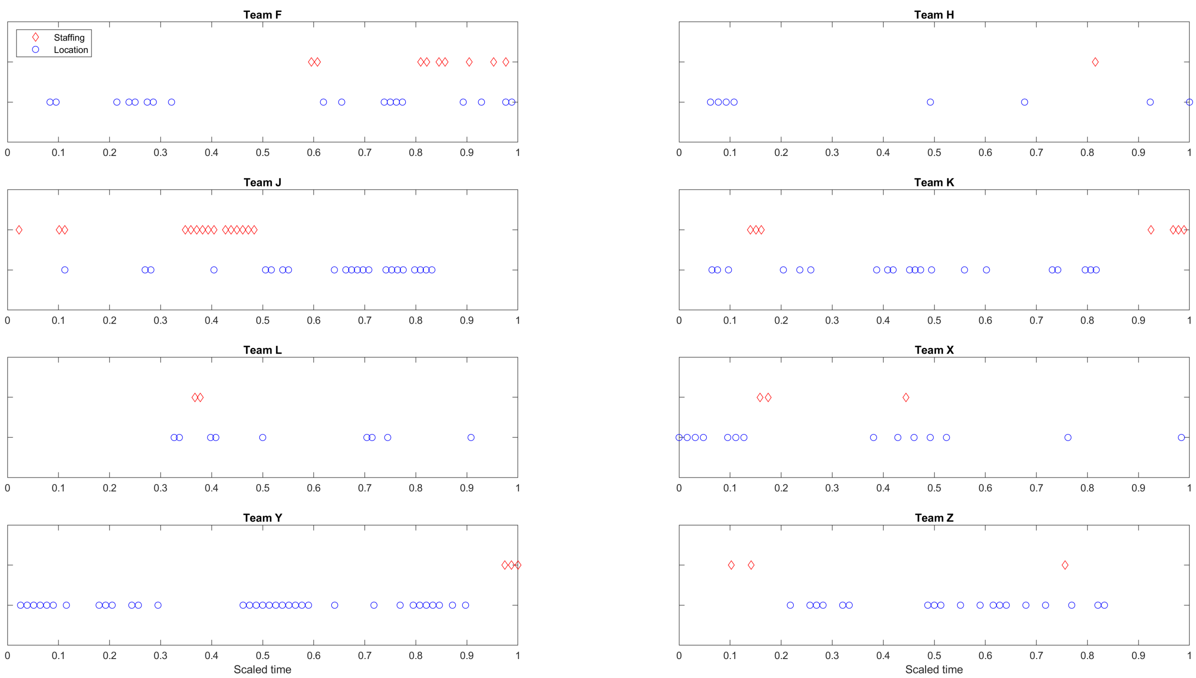

Figure 4. Time segments in which each team discussed two or more variables from a staffing subproblem (red diamonds) or a location subproblem (blue circles). The time axis is scaled.

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5.3 Common pair analysis

The results of common pairs show all teams except Team H mostly decomposed common pairs to location and staffing. All teams have one large interconnected network of common pairs of location, size, and spatial flow pattern or other high level variables. Since decisions on size of manufacturing areas and spatial flow pattern are related to location variables, it is expected these variables are discussed on the same time segments. All teams (except Team H) have one to five common pairs of staffing variables all separated from location common pairs. In addition to these common pairs of location and staffing, there are four other common pairs among all teams including one size and one high level variables by Team H, one internal layout and one high level variables by Team Y.

5.4 Common triplet analysis

The results of the triplet analysis show that each team has one large interconnected network of variables that are mostly location variables. Four teams discussed a triplet with three location variables (numbers 23, 34, and 35) for three assembly operations that were close to each other in the manufacturing process. Three teams have a triplet with the “Spatial flow pattern” variable (number 69) and location variables. Five teams discussed triplets with staffing variables, which created a subgraph of seven staffing variables (shown in Figure 1b). No common triplets included both location and staffing variables. Overall, the triplet results show that the teams decomposed the problem into location subproblems and staffing subproblems.

5.5 Similarity among subproblems

To consider the similarities across the different teams, we looked at “small” subproblems (those with three or four variables) and identified other subproblems that share at least three of the variables with the small subproblem. (In total, the eight teams discussed 127 subproblems; of these, 61 had only three or four variables.) Table 1 displays the results for the 30 small subproblems that had some overlap (at least three common variables) with other subproblems. Subproblems considered by different teams had some overlap. At the extreme, the variables in a small subproblem were also included in up to five other subproblems across five teams. Over half of the small subproblems that were similar to other subproblems focused on location variables (18 of 30).

Table 1. Similarities between “small” subproblems and other subproblems. Each row corresponds to one small subproblem, which is identified with bold type. The other subproblems on the same line have at least three of these variables as well. The “Type” indicates the type of the small subproblem: Loc = Location, Sta = Staffing, InL = Internal layout, Siz = Size, blank = no type.

Type	F	H	J	K	L	X	Y	Z
Loc	**F.9**						Y.17	
Loc	F.8	**H.3**	J.3, J.8			X.9	Y.5	
-		**H.9**						Z.14
Loc	F.8	**H.10**				X.5		
-		**H.12**					Y.17	
Loc			**J.1**	K.1			Y.5	
Loc			J.1	**K.1**			Y.5	
Sta			J.6	**K.8**	L.5			
Loc		H.2	J.9	K.10, **K.11**		X.5	Y.5	
Loc			J.3	**K.13**				Z.8
Loc			J.8	**K.15**				
Loc			J.9	**K.16**			Y.5	
-				**K.18**				Z.14
-				**K.19**			Y.5	
Loc			J.8	**K.20**				
InL					**L.3**			Z.14
Loc				K.5	**L.6**	X.5		
-			J.3		**L.9**		Y.5	
Loc	F.8		J.3		**L.15**			
Loc	F.8				**L.16**			
-						**X.1**	Y.17	
Loc		H.3	J.8			**X.9**	Y.17	Z.17
-						**X.11**	Y.17	
-			J.7				**Y.1**	
Sta					L.4		**Y.10**	
Loc	F.8	H.2	J.3			X.5	**Y.20**	
Loc				K.10			Y.17	**Z.3**, Z.8
Siz						X.15		**Z.4**
Loc			J.3, J.8				Y.5	**Z.11**
Loc			J.8			X.9		**Z.17**

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6 DISCUSSION

The results suggest several general observations. First, the formation of subproblems was driven by either (a) the interdependence of the variables or (b) their similar lack of interdependence with other variables. For example, many subproblems were focused on laying out a set of adjacent process steps in one area of the factory; locating each area is dependent on the locations of the others since materials must travel frequently between them. Similarly, many subproblems were focused on the allocation of a scarce resource, such as staffing, across multiple areas; these are also interdependent because staff allocated to one area cannot then be allocated to another. These are examples of subproblems driven by (a) interdependence of variables. However, another set of subproblems were formed from variables that have little interdependence with any other variables; it is interesting that these variables were also considered together. Some similarities between subproblems from different teams (especially location subproblems) were shown in Table 1.

The second general observation is the decoupling of decisions about the two main scarce resources: location (space on the factory floor) and staffing. Teams discussed each of these at different times, and rarely did these types of variables appear together in a common pair or triplet.

The third general observation is that, despite these similarities, the teams' design processes also varied greatly. Few teams used the same subproblems. They discussed staffing and layout at different times and in different orders. Nevertheless, a fourth general observation is that all the teams did some form of decomposition. No teams tried to consider all variables together all the time, nor to work on just one variable at a time.

Despite the teams' unstructured design processes, our analysis found that the teams identified similar key aspects of the design problem (such as the interdependent variables) and used those to structure their decision-making processes with similar subproblems. The differences suggest that the teams did not consistently or thoroughly analyze the design problem, however, perhaps due to its unfamiliarity, the limited time available, and the lack of prior collaboration.

The differences among the teams suggest that design teams might benefit from more guidance about decomposing complex design problems. Although experienced engineers have developed intuition about this process, the diversity that we observed in this study suggests that they have not converged on a single superior approach. There might be an opportunity for finding an approach that can support teams in completing complex design problems more efficiently and effectively.

7 SUMMARY AND CONCLUSIONS

This paper described an in-depth study of the decision-making processes that teams of professionals used to design a complex system. The variables that they discussed and the subproblems that they considered were analyzed in multiple, interrelated ways to identify the similarities and differences across the teams. The teams were given the same design challenge, and their design processes showed some similarities: some interrelated sets of variables appeared together in subproblems for multiple teams, and the teams considered location subproblems and staffing subproblems separately. Still, there were many differences among the subproblems and when the teams considered them, which suggests there is an opportunity to improve upon their approaches.

Overall, these results show that teams separated the design problem into subproblems and solved these subproblems mostly independently. Future research could address some of the limitations of this research, including the small set of teams and the focus on one type of design problem in one domain. Additional research is needed to determine if there are correlations between the characteristics of the design process and the quality of the solutions that are generated. Further research could also explore whether solvers' decomposition of a design problem mirrors the structure of the problem, as it tends to do in product development organizations (Sosa et al., 2004; Colfer and Baldwin, 2016).

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