MODELLING PROPORTIONS AND SEQUENCES OF OPERATIONS IN TEAM DESIGN ACTIVITIES

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ABSTRACT

The presented research aims at modelling and formalising the process of team design activity as an interplay between the evolution of design problems and solutions. The motivation founds primarily on a presumption that there exist regularities in designing which can be captured and formalised using the appropriate models. The study thus investigates whether the identified design operation proportions and sequence probabilities are consistent throughout the different parts of team conceptual design activities. It does so by exploring the utility of mathematical models built based on the correlations and statistically significant sequences underlying the previously identified designing patterns. The developed mathematical model was tested by replicating moving-average analyses of design operation proportions and sequences, which were originally observed in the protocol analysis study. A close fit was found between the simulated and the observed data, particularly in providing insights regarding operation patterns and proportion trends. The presented models and modelling methodology are potentially an appropriate means for the next steps in describing, and consequently predicting and supporting team design activity dynamics.

Keywords: Design process, Design operations, Process modelling, Teamwork, Process patterns

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1 INTRODUCTION

In engineering design, team collaboration becomes essential when no single actor has all the time, knowledge, skills, or inspiration needed to realise a particular design task. As such, design teamwork can provide numerous advantages over individual designing and has thus far been related to different desirable outcomes such as improved problem solving and product quality, and the reduction of development time and costs (Crowder et al., 2012; Hsu, 2017). Therefore, being able to work in a team has been perceived as one of the core design competencies (Robinson et al., 2005), whereas the engineering design education increasingly encompasses learning outcomes related to communication and teamwork, in order to prepare design students for the design tasks that emerge in the real-world, professional product development context (Han et al., 2018; Hultén et al., 2018).

Despite the increasing research interest, there remain aspects of designing in teams that lack adequate support, especially when it comes in the form of computational tools. This has been particularly evident in the conceptual design stage of product development (Maarten Bonnema and van Houten, 2006), during the critical activities such as ideation (Shah et al., 2000) and design review (Vuletic et al., 2018). Namely, the tools for collaborative design may often fail in supporting effective communication of ideas and information, which is largely due to the insufficiently understood information flows in design teams (Ostergaard and Summers, 2009). Modelling of the actual design processes has thus become essential for understanding the dynamics of designing in teams, as well as developing tools that could assist collaborative designing (Goldschmidt, 2014; Ostergaard and Summers, 2009), that is support design teams in formulating design problems and providing solutions to these problems.

In order to better predict these team dynamics and support designing in teams, here presented research aims at modelling and formalising the process of team design activity as an interplay between the evolution of design problems and solutions. The motivation founds primarily on a presumption that there exist regularities in designing that transcend any individuals involved in the process (Gero and Kan, 2016; Gero and Kannengiesser, 2014), and that these regularities can be captured and modelled.

The authors' initial efforts of modelling team conceptual design activity (Martinec et al., 2019) have resulted in theoretical developments of a state-transition model and initial empirical evidence of designing patterns that can be identified using the model. The follow-up study (Martinec et al., 2020) delved deeper into the data and found correlations between proportions of different types of design operations as well as the most probable sequences of design operation pairs during team design activities. Here presented study builds on these qualitative and quantitative insights, primarily by adding the temporal aspect into modelling of proportions and sequences of design operations across the problem and the solution space. More precisely, it addresses the following research question: *Are the identified design operation proportions and sequence probabilities consistent throughout the different parts of team conceptual design activities?* It does so by exploring the utility of mathematical models built based on the correlations and statistically significant sequences underlying the previously identified designing patterns. As such, the presented study represents a research step towards the ultimate goal of simulating team activity and identifying the sequences of design operations that are more likely to stimulate the desirable problem-solution co-evolution patterns. Design practitioners could utilise the identified sequences as guidelines for steering the design process and improve problem-solving efficiency.

2 BACKGROUND

The here presented investigation of team conceptual design activity has been based on a state-transition model which captures sequences of design operations performed to explore the design space (Martinec et al., 2019). The model combines three perspectives on the design process:

- Designing is modelled as a state-transition process (Reymen et al., 2006). Design space evolution is represented by a set of states, whereas design operations describe transformations of one state to another. Designing thus involves both the change of the states of the product being designed (design space evolution), and the change in the state of the design process (design operation sequences).
- Design space evolution implies the co-evolution of the design problem and the design solution, that is the co-evolution of the problem and the solution space (see, e.g. Dorst and Cross, 2001). The first consists of problem entities, such as requirements, constraints and needs and the latter consists of

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solution entities, such as solution ideas, concepts and working principles. Designers and design teams explore both spaces and keep switching between them throughout the design process.

- Three fundamental types of design operations are performed within both the problem and the solution space - analysis, synthesis, and evaluation (ASE). These operations can be found across various prescriptive and descriptive models of design (examples include Fiorineschi et al., 2016; Gero and Jiang, 2015; Mc Neill et al., 1998; Stempfle and Badke-Schaub, 2002; Wodehouse and Ion, 2010). Within the state-transition model, analysis has been defined as a state transition resulting in a change in the level of understanding of a particular design entity within the explored design space (problem or solution). Synthesis has been defined as a state transition resulting in the appearance of a new design entity within the explored design space. Finally, evaluation has been defined as a state transition resulting in the assessed appropriacy of a particular design entity within the explored design space. Please consult Martinec et al. (2020) for more detailed definitions.

The developed state-transition model thus enables capturing of various sequences of ASE design operations performed within and in-between the problem and the solution space during design activities. The model was first used to explore patterns of ASE and their role in problem-solution co-evolution (Martinec et al., 2019). The study identified three patterns specific for team ideation and concept review activities: the alternation of solution synthesis and analysis, the sequences of synthesis, analysis and evaluation within solution space, and the potential co-evolution episodes characterised by switching spaces to synthesise new design entities. In addition, the use of the state-transition model enabled identification of significant differences in proportions of design operations when comparing team ideation and concept review activities. Ideation was characterised as a divergent activity, due to higher proportions of problem-related design operations and solution synthesis, in contrast to the convergent concept review activity, which exhibited higher proportions of solution analysis and evaluation.

The follow-up study (Martinec et al., 2020) utilised the model to revisit some of the literature-drawn assumptions regarding modelling of ASE and problem-solution co-evolution. Firstly, it investigated the relationship between ASE and problem/solution-related design operations. A strong negative correlation was found between proportions of analysis and problem-related design operations, in addition to the strong negative correlation between proportions of synthesis and solution-related design operations, and a strong positive correlation between proportions of evaluation and solution-related design operations. Secondly, it identified the dominant sequences of ASE in team design activity, with synthesis being the most probable design operation to follow analysis and analysis being the most probable design operation to follow synthesis. Thirdly, the model was used to analyse the nature of transitions in-between the problem and the solution space. It showed that both the new problem entities and solution entities are most likely to be synthesised following solution space exploration.

Besides revealing inconsistencies in how ASE are defined and interpreted across the literature, the two studies demonstrated patterns which cannot be described by some of the well-accepted design models. Here presented study builds on these insights by formalising the relationships between design operation proportions and sequences using regression modelling and investigating pattern consistency given the temporal aspect of team conceptual design activities.

3 EMPIRICAL DATASET AND ANALYSIS

The study employs an empirical dataset comprised of protocol strings of eight team design sessions. The dataset originates from the experiments designed and conducted by Cash et al. (2013). The eight experiment sessions correspond to four teams performing two types of conceptual design activities. The first activity was ideation, with a goal of devising as many concept ideas for mounting a camera on a remotely operated balloon as possible. In the second activity, the teams would meet again to review the elaborated concepts, select a single concept or combination of concepts, and refine them into a final concept solution. Each team consisted of three mechanical engineering students selected from a final year product design and development course and was given 50 minutes for both sessions.

The recordings were segmented and coded using a coding scheme that combines ASE and problem-solution spaces (Martinec et al. 2019). Six types of design operations have been coded: problem analysis (PA), problem synthesis (PS), problem evaluation (PE), solution analysis (SA), solution synthesis (SS) and solution evaluation (SE). The resulting protocols represent strings of segments (instances) where design teams either analysed, synthesised, or evaluated problem and solution entities (on average 293 segments for ideation and 280 for concept review activity). The previous protocol

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studies have utilised two main analysis measures, each of which can be applied to the entire protocol or to protocol fragments, whose size depends on the type of the analysis:

- Proportions of design operations - instances of a particular type of design operation are counted and divided by the total number of segments within the analysed fragment of the activity protocol. Symbol: p_x (proportion of design operation x), measured in %.
- Proportions of design operation sequences - all combinations of instances of two consecutive design operations are counted and divided by the total number of transitions between design operations within the analysed fragment of the activity protocol. Symbol: $p_{x,y}$ (proportion of transitions from design operation x to design operation y), measured in %.

Given the regularities which have thus far been identified in the data, the main motivation was to formalise the relationships between proportions and sequences of different types of design operations. The formalised relationships would then form a mathematical model underlying the potential simulation and support tools. A regression analysis was conducted to quantify the relationships (Teetor, 2011) between the measured proportions. More precisely, linear and polynomial regression analysis were performed to investigate the relationships between proportions and sequences of design operations. The linear regression approach is simple to apply but assumes that the variables in the regression are linear and that the effect of independent variables is constant throughout the entire range of the response variable (Chan et al., 2011). Polynomial regression is (from here on) considered a special case of multiple linear regression. A total of three fundamental independent variables have been identified: one variable which defines the ratio of proportions of problem- and solution-related design operations, and two variables which define the distribution of ASE, e.g., the proportion of analysis and synthesis (in that case the proportion of evaluation can be deducted). These three independent variables thus represent the input parameters needed for calculating (predicting) the dependent variables, that is the proportions and probabilities of sequences of ASE design operation within and in-between the problem and the solution space (e.g. using computational simulation tools). For the sake of simplicity, the regression has been performed using the proportions of analysis, synthesis, and evaluation ($p_A + p_S + p_E = 1$), and the proportions of problem- and solution-related design operations ($p_{PRO} + p_{SOL} = 1$).

Since the effects of intercepts have not been found significant, they were excluded from the regression analysis. In this way, only one coefficient is sufficient to describe a particular relationship. Moreover, the regression models include only interactions terms or squared terms (without including the main effects). There are two reasons for this. First, the main effects have in general not been found significant. Second, the modelling purpose is solely to predict proportions of design operations and their sequences, rather than statistical inference about each of the effects. The normality of the error distribution in the regression models was tested using the Shapiro-Wilk test. Other linear regression diagnostics have been performed by plotting diagnostic plots (observed vs. predicted values, residuals vs. predicted values).

4 REGRESSION MODELLING

The presented analysis approach samples different fragments of the activity protocols and analyses if regularities can be identified and modelled across different points in team design activity (the temporal aspect). The initial number of data points was relatively small (one point per observed experiment session) and corresponded only to the average proportions of design operations during an activity. The number of data points was increased by splitting every protocol string into three equal fragments (the beginning, the middle and the end of the activity), each representing an individual string for the analysis. The rationale for splitting the protocol strings lies in the assumption that the hypothesised regularities should be consistent for different fragments of the activity. The splitting resulted in a total of 24 data points that were used for regression modelling. The fragmented protocol strings vary in length from 73 to 114 segments, which is sufficient for calculating the proportions of design operations and their sequences. Nevertheless, the regression modelling was performed for both the initial 8 and the fragmented 24 data points, in order to check the consistency of the results. The relationship between proportions was consistent regardless of the data point number. In fact, the higher the number of instances of a particular design operation in a protocol fragment, the less significant difference exists between the two cases of linear regression (8 vs. 24 data points). For example, solution analysis, synthesis, and evaluation design operations, which were the most frequent instances on average, exhibit only 0.1%, 0.2% and 0.2% difference respectively, whereas problem evaluation as

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the least frequent instance manifests 5.2% difference. Hence, increasing the number of data points by splitting the initial protocol strings into smaller fragments can be performed as long as a sufficient number of instances of each design operation is present within the fragments to calculate the introduced measures.

The regression modelling is reported in two parts. First, the proportions of six types of design operations (p_{PA}, p_{PS}, p_{PE}, p_{SA}, p_{SS} and p_{SE}) are formulated as functions of ASE proportions (p_A, p_S, p_E) and the proportions of the problem- (p_{PRO}) and solution-related (p_{SOL}) design operations. Second, the proportions of sequences of two design operations are formulated as functions of design operation proportions (both aggregated – e.g. $p_{A,A}$, $p_{A,S}$, $p_{PRO,PRO}$, etc. – and unaggregated – e.g. $p_{PA,PA}$, $p_{PA,PS}$, etc.).

4.1 Modelling proportions of design operations

Several iterations of linear regression modelling were conducted on the protocol data. The best fit was reached for the following hypothesised relationship: *The proportion of either one of ASE design operations within the problem or the solution space is proportional to the product of the corresponding proportions of ASE and problem/solution-related design operations.* Symbolically, the formulated relationship can be written as shown in Equation 1.

$$p_{xy} = k_{xy} \cdot p_x \cdot p_y, \qquad x = \{PRO;SOL\}, \quad y = \{A;S;E\} \tag{1}$$

Multiple linear regressions were calculated to predict the proportions of the six design operation types based on the interaction of ASE and problem/solution proportions (see Figure 1). Significant regression equations were found (p-value of at least p<0.001) with R^2 ranging from 0.906 to 0.996. This means that, for example, the interaction of proportions of analysis and problem-related design operations significantly predicted the proportion of problem analysis. Shapiro-Wilk test failed to reject the normality assumption for any of the models at the significance level of 0.05.

The equations listed in Figure 1 enable modelling of proportions of six ASE design operations in problem and solution space based on the three independent variables.

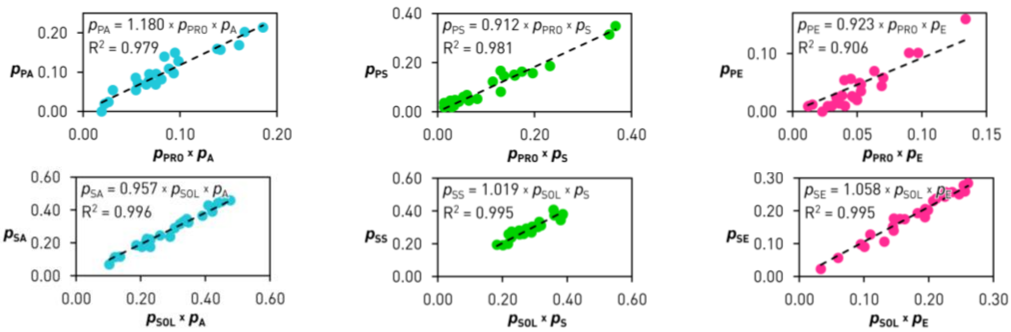

Figure 1. Proportions of six design operations types (top: p_{PA}, p_{PS}, p_{PE}; bottom: p_{SA}, p_{SS}, p_{SE}) as functions of corresponding proportions of ASE and problem/solution proportions

4.2 Modelling sequences of design operations

The modelling of sequence proportions was conducted in a similar manner as modelling proportions of design operations. The hypothesised relationship was that the proportions of moves between two design operations are proportional to the product of proportions of these two design operations.

4.2.1 Sequences of analysis, synthesis, and evaluation design operations

The modelling was first conducted for the proportions of moves between analysis, synthesis, and evaluation (design operations aggregated into ASE). The following relationship has been hypothesised based on the regression modelling best fit: *The proportion of moves between two ASE design operations is proportional to the product of the corresponding proportions of ASE design operations.* Symbolically, this relationship can be written as shown in Equation 2.

$$p_{x,y} = k_{x,y} \cdot p_x \cdot p_y, \qquad x,y = \{A;S;E\} \tag{2}$$

Simple linear regressions were calculated to predict the proportions of sequences of two ASE design operations based on the squared proportion of the corresponding ASE proportions (see Figure 2). Significant regression equations were found (p-value of at least p<0.001) with R^2 ranging from 0.824 to 0.984. This means that, for example, the interaction of proportions of analysis and synthesis design

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operations significantly predicted the proportion of analysis to synthesis, as well as synthesis to analysis sequences. Shapiro-Wilk test failed to reject the normality assumption for all models at the significance level of 0.05, except for the analysis to analysis and evaluation to evaluation sequences.

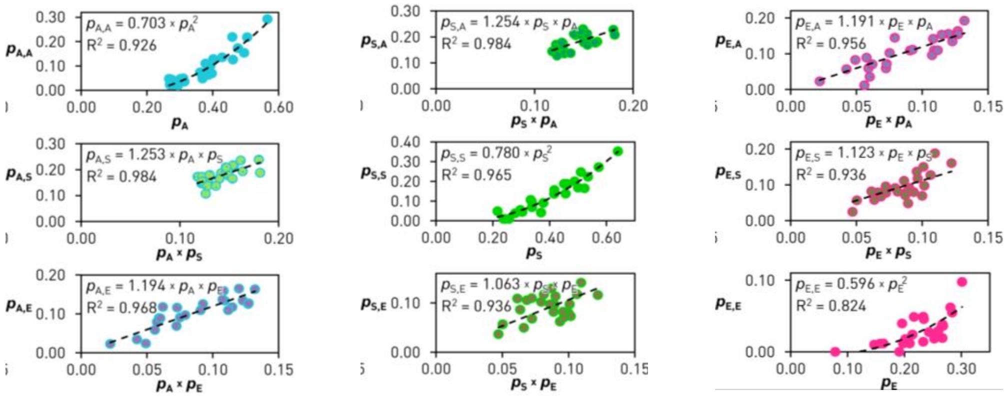

Figure 2. Proportions of ASE sequences as functions of corresponding proportions of ASE

The equations in Figure 2 enable modelling of proportions of nine possible sequences of two ASE design operations based on the three independent variables. Nevertheless, the normality of residuals assumption has been violated for two regression models; hence the corresponding sequence proportions must be deducted from the models for which the normality assumption was not rejected.

4.2.2 Sequences of problem- and solution-related design operations

The subsequent regression analysis considered sequences of two design operations aggregated into problem- and solution-related design operations. The following relationship has been hypothesised based on the regression modelling best fit: *The proportion of moves in the problem or the solution space is proportional to the squared proportions of the corresponding problem- or solution-related design operations.* Symbolically, this relationship can be written as shown in Equations 3 and 4.

$$p_{x,x} = k_{x,x} \cdot p_x^{\ 2}, \qquad x = \{PRO; SOL\} \tag{3}$$

$$p_{x,y} = p_y - p_{y,y} = k1_{x,y} \cdot p_y^{\ 2} + k2_{x,y} \cdot p_y, \qquad x,y = \{PRO; SOL\},\ x \neq y \tag{4}$$

Simple and multiple linear regressions were calculated to predict the proportions of sequences of moves within and in-between the problem and the solution space based on the squared proportion of the corresponding proportions (see Figure 3). Significant regression equations were found (p-value of at least $p<0.001$) with R^2 ranging from 0.947 to 0.988. This means that, for example, the squared proportion of problem-related design operations significantly predicted the proportion of sequences within the problem space. Shapiro-Wilk test failed to reject the normality assumption for any of the models at the significance level of 0.05.

The equations in Figure 3 enable modelling of proportions of four possible sequences of problem- and solution-related design operations based on the three independent variables.

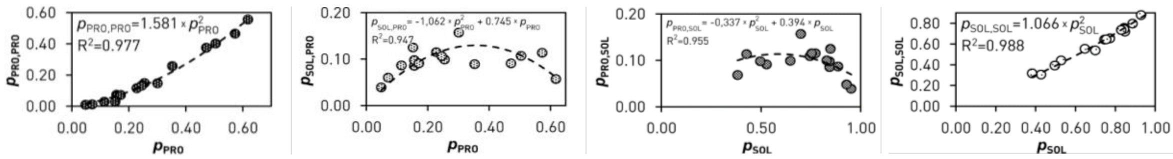

Figure 3. Proportions of design operation sequences within and in-between problem and solution space as functions of corresponding problem/solution proportions

4.2.3 Sequences of ASE design operations within problem and solution space

Finally, regression analysis has also been conducted to model sequences of ASE design operations within and in-between the problem and the solution space. In this step, the previously reported regression models of sequences of design operations aggregated into ASE and problem/solution-related are utilised as independent variables. At the core, this procedure is identical to formulating the relationships of proportions of ASE design operations in the problem and the solution space and the proportions of ASE and problem/solution-related design operations.

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Hence, a hypothesised relationship is formulated as follows: *Proportions of moves between two ASE design operations within and in-between the problem and the solution space are proportional to the product of the corresponding proportions of moves between ASE and the proportions of moves between the problem/solution-related design operations.* Symbolically, this relationship can be written as shown in Equation 5.

$$p_{\mathrm{xw,yz}} = k_{\mathrm{xw,yz}} \cdot p_{\mathrm{xw}} \cdot p_{\mathrm{yz}}, \qquad \mathrm{x,y} = \{\mathrm{PRO;SOL}\}, \quad \mathrm{w,z} = \{\mathrm{A;S;E}\} \tag{5}$$

Due to a relatively large number of possible sequences, the results of the linear regression modelling have not been presented as part of this paper. Unlike the case with previously reported models, linear regression modelling has been conducted using only 8 data points, that is without splitting the initial protocol strings. The reason for this is that due to the smaller number of sequences, the shorter fragments of protocol strings do not contain all possible instances of sequences of two design operations, making the results unreliable.

The effect of the lower number of particular instances of design operations sequences (e.g., instances where teams moved from solution space to problem evaluation) is reflected in lower R^2 values of the resulting regression equations. For example, no significant equations were found for the problem synthesis - solution evaluation, solution synthesis - problem evaluation and solution evaluation - problem evaluation moves (p-value > 0.05). In addition, the Shapiro-Wilk test rejected the assumption of normality for a total of eight design operations sequences ($p_{\mathrm{PA,SA}}$, $p_{\mathrm{PA,SS}}$, $p_{\mathrm{PS,PS}}$, $p_{\mathrm{PE,PS}}$, $p_{\mathrm{PE,PE}}$, $p_{\mathrm{SS,PE}}$, $p_{\mathrm{SE,PS}}$, $p_{\mathrm{SE,PE}}$), so again the corresponding sequence proportions must be deducted from the models for which the normality assumption was not rejected.

The 36 regression equations enable myriads of investigations to be performed and are, as such, particularly valuable addition to the mathematical model. Among other things, the response provided by the equations can be used to perform moving average analysis of ASE design operations sequences within and in-between the problem and the solution space, as shown in the following section.

5 MODEL TESTING

The formulated linear regression equations enable prediction of average proportions of design operations and their sequences within a design activity or its fragments. The integration of these equations within the existing theoretical framework allows formulation of a mathematical model for calculating proportions of design operations and their sequences based on three input parameters (two to define proportions of ASE and one to define proportions of problem/solution-related design operations).

The proposed mathematical model relies both on the regression equations with a high goodness of fit (high R^2 values), which do not violate the normality of residuals assumption (based on the Shapiro-Wilk test), as well as the theoretical foundations of state-transitions proportions and sequences. For example, the individual models regarding the proportions of solution analysis, synthesis, and evaluation exhibit higher R^2 values when compared to problem analysis, synthesis, and evaluation. Hence, the latter can be calculated as shown in Equation 6.

$$p_{\mathrm{PA}} = p_{\mathrm{A}} - p_{\mathrm{SA}}; \quad p_{\mathrm{PS}} = p_{\mathrm{S}} - p_{\mathrm{SS}}; \quad p_{\mathrm{PE}} = p_{\mathrm{E}} - p_{\mathrm{SE}} \tag{6}$$

Similar procedure can be applied for all the remaining equations with relatively lower R^2 values or violation of the residual normality assumption. For example, given enough design operation instances, the sum of sequence proportions that either start or end with analysis can be formulated as equal to the overall proportion of the analysis design operation. Such argumentation is vital as it allows taking advantage of only the regression equations with the highest prediction ability.

Hence, the resulting set of equations encompassed within the mathematical model results either from regression modelling or from the theoretical assumptions. The mathematical model developed in such a way was first employed to compute moving average proportions of design operations and sequences of design operations for a given average ASE and problem/solution proportions. Namely, to test the prediction ability of the developed mathematical model, the input parameters have been sampled from the moving average proportions of ASE and problem/solution-related design operations obtained from the protocol analysis study of team conceptual design activities. The width of the moving average sample window was set to 15% of the total number of segments. Only three predicated independent variables have been sampled from the original dataset (proportions of analysis, synthesis, and problem-related design operations). The mathematical model uses the three independent variables to compute (predict) proportions of design operations and their sequences for a particular moving window.

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Examples of the investigation of the mathematical model's predictive power are displayed across Figures 4-7. The figures provide qualitative comparison of patterns and trends related to the observed and computed proportions and sequences of design operations for the same time frame. Due to the limited space available, only one example for each of the proportion and sequence aspects has been shown.

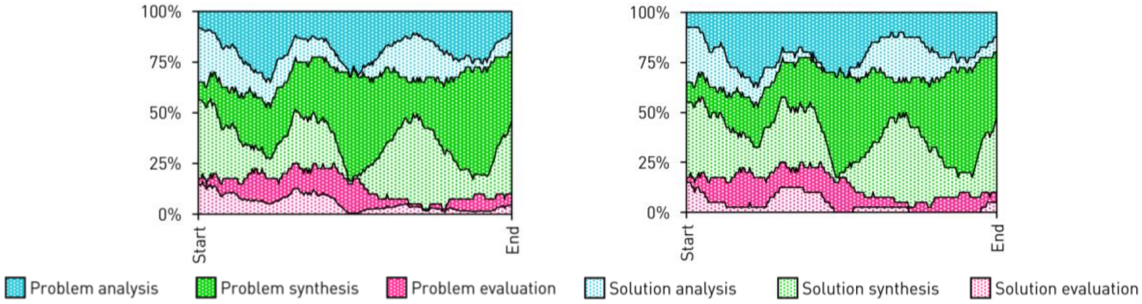

Figure 4. Team 1 performing ideation activity: Moving-average analysis of design operation proportions based on observed (left) and predicted data (right)

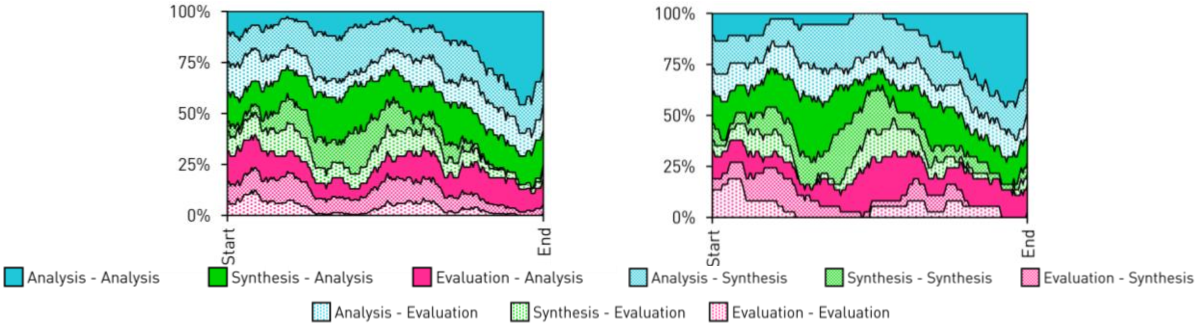

Figure 5. Team 2 performing concept review activity: Moving-average analysis of ASE sequence proportions based on observed (left) and predicted data (right)

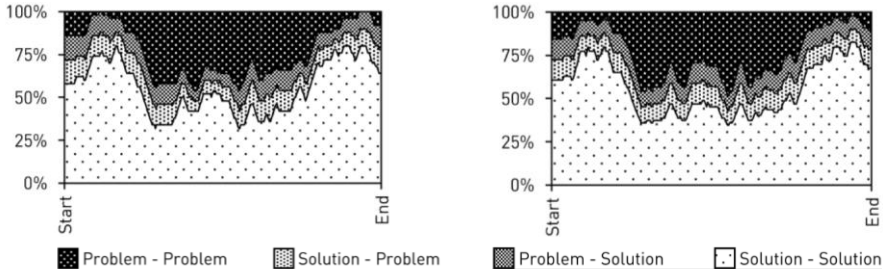

Figure 6. Team 3 performing ideation activity: Moving-average analysis of problem-solution sequence proportions based on observed (left) and predicted data (right)

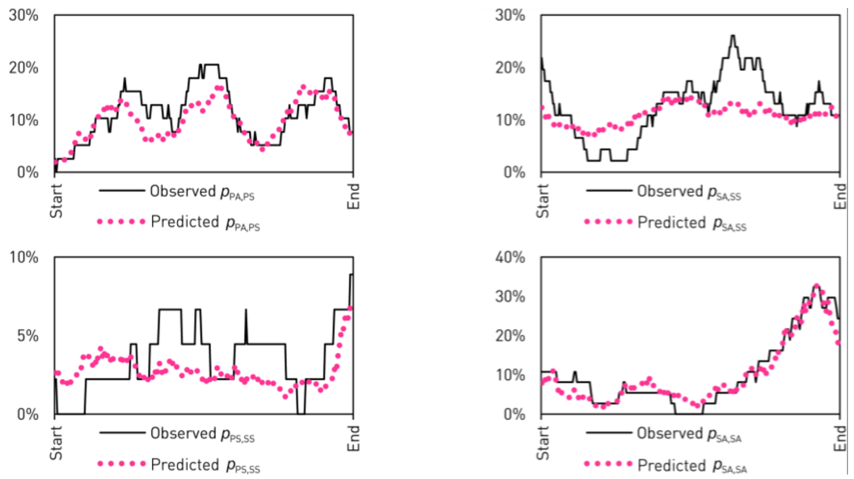

Figure 7. Teams 1 (upper) and 2 (lower) performing ideation (left) and concept review (right) activities: Moving-average analysis of design operation sequence proportions based on observed (full line) and predicted data (dotted line)

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6 DISCUSSION AND CONCLUSION

The changes in proportions of observed design operations and their sequences have to a large degree been satisfactorily replicated using the mathematical model (qualitative assessment based on the graphs shown across Figures 4-7). It can be argued that the predicted proportions coincide with the teams' processes measured via protocol analysis, particularly in the case of predicting the proportions of the six types of design operations (Figure 4), as well as for computing the proportions of sequences of design operations aggregated to ASE (Figure 5) and problem/solution-related (Figure 6). The correspondence between the observed and predicted data is less satisfactory for the sequences of design operations within and in-between the problem and the solution space (Figure 7). Namely, some of the regression models fail to precisely reflect the moving average spikes, that is the major changes in moving average proportions of certain design operation sequences appearing in-between a relatively small number of protocol segments. It can be argued that the lower fit of the last group of regression models is due to the smaller number of data points (8 vs. 24 used for the first three groups). Also, the lower fit is even more noticeable for the sequences which have rarely appeared during the protocol analysis study. It must be noted that the conceptualisation of the mathematical model as a support tool is to provide insights regarding the patterns and trends (formulated by means of regression equations) in performing different design operations, rather than precise percentages. As such, the presented models, as well as the "from observation to modelling" methodology are potentially the appropriate means for the next steps in describing, and consequently predicting and supporting team design activity dynamics.

Previous attempts aimed at formalising design activity patterns were focused solely on modelling relationships between the activity progress and the proportions or sequences of design moves. For example, Gero and Jiang (2015) used a simple linear regression model to depict the increasing or decreasing trend of designers' cognitive focus on problem/solution reasoning. Mc Neill et al. (1998) employed linear regression to test the slope of function-behaviour-structure and analysis-synthesis-evaluation proportions and sequences given the activity progress. Models shown in both examples exhibit relatively fit and are as such used solely as means of process comparison, rather than a process prediction (simulation) tool. On the other hand, models aimed specifically at simulating design processes, such as Markov Chain, agent-based or deep learning models (see, e.g. McComb et al., 2017; Raina et al., 2019) show better flexibility when it comes to predicting or imitating sequences of design operations, but are typically context dependent or trained for a specific types of design tasks.

Here proposed modelling approach can be used as an adaptation layer for the existing design operation models, as it formalises the sequence probabilities regardless of the activity progress or task type. For example, rather than using a fixed transition matrix when simulating designing as a Markov process, the mathematical model can be used to adjust the matrix given the ASE and problem/solution proportions in the given activity fragment. Moreover, the approach can be utilised to identify the most favourable sequences of design operations in a given situation (e.g., to maximise problem-solution co-evolution during ideation, or convergence during concept review) and thus help readjusting, or sort of steering the design process. Thus, rather than simulating human designers, the tool would follow their progress and adapt the support based on the theoretical models and observed data. In addition, the mathematical models based on observational data can be used as means of simulating proportions and sequences of design operations for any predefined setup of team conceptual design process. It is hence hypothesised that the proposed approach (theoretical state-transition model and the mathematical modelling procedure) can be utilised to capture design operation regularities in team design activities and support design teams in planning their steps by proposing the optimised design patterns for a given situation.

Of course, the predictive power of the underlying regression models would rely primarily on high quality data. Given that here presented models result from a relatively small sample, it must be emphasised that the formalised proportions and probabilities are not applicable to different team compositions, different types of products being designed or different types of design activities. Nevertheless, the presented modelling approach, which is also the main contribution of the paper, can be applied to a variety of other design activity contexts. Hence, a number of context-specific models could be created and calibrated to describe and predict the behaviour across different development environments.

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