INTERNATIONAL DESIGN CONFERENCE - DESIGN 2012
Dubrovnik - Croatia, May 21 - 24, 2012.

CORRELATION OF STRUCTURAL CHARACTERISTICS OF PRODUCT DESIGN STRUCTURE MATRICES

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Keywords: design structure matrix, product model, structural analysis, structural characteristics

1. Challenges when selecting structural analysis criteria

Structural considerations are an established approach to manage complexity. One of the most used methods in engineering design is the design structure matrix (DSM) [Browning 2001]. It has been applied to products, organizations, processes and parameters [Browning 2001]. Its analytical capabilities have been supplemented by graph theory [Maurer 2007] and network analysis [Kreimeyer 2010]. Its modelling capabilities have been supplemented by the domain mapping matrix (DMM) and the multiple-domain matrix (MDM) [Maurer 2007]. Maurer has proposed a structural approach to deal with complexity in technical systems [Maurer 2007]. Figure 1 shows a shortened version of the approach which is focussed on the modelling and analysis part of the approach.
Manifold structural analysis criteria have been proposed in complex systems research. They are from graph theory [Gross and Yellen 2005], network analysis [Cami and Deo 2008], and motif analysis [Milo et al. 2002]. The criteria comprise properties of entire structures like planarity or connectedness, subsets of structures like cycles or clusters, metrics like degree or relational density and visualizations like matrices, graphs or portfolios. [Maurer 2007] and [Kreimeyer 2010] have proposed collections of structural criteria. Especially, the introduction of motif analysis has led to an almost infinite variety of structural criteria. There is no shortage of computable criteria but a shortage of guidance in finding the meaningful and helpful criteria. Thus, the need for careful selection of analysis criteria arises.

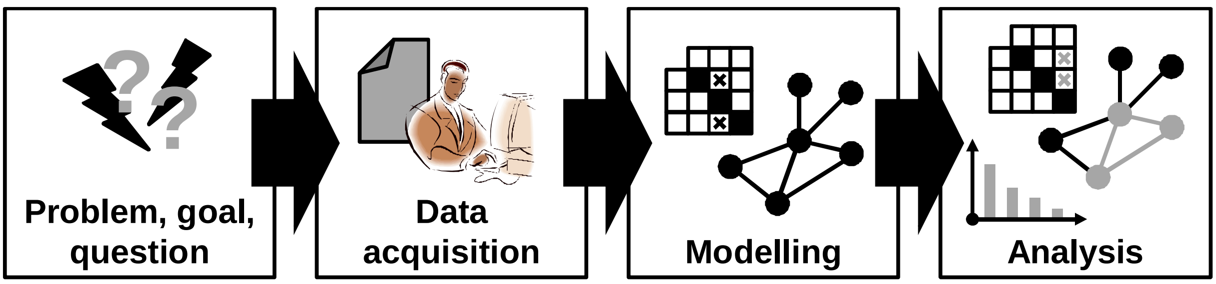

Figure 1. Context of this research

To support the selection of structural analysis criteria [Biedermann and Lindemann 2011a] developed a procedure to design structural analysis scenarios. The scenario links problems and analysis goal to the necessary model of the structure and the analysis criteria. It provides guidance through the modelling and analysis process. The procedure has two major tasks. First, the applicability of the criteria has to be determined. In other words, it must be assessed what can reasonably be deduced from the structural analysis results. [Biedermann and Lindemann 2011b] give requirements for applicability and show how they can be tested. The second major task is to check the consistency and redundancy of the analysis results. [Biedermann and Lindemann 2011a] introduce a tool to support the checks. It uses the dependencies among the criteria which are derived from the criteria's definitions. However, no result takes the system or its model into account. This paper aims at overcoming this obstacle. The main aim is the reduction of the number of analysis criteria. We approach this aim by identifying dependencies among the criteria which arise from the modelled system. These dependencies form clusters. For each cluster we identify criteria which can represent the cluster. Thus we reduce the number of criteria. To identify the dependencies we analyse several models representing products and perform a correlation analysis of the resulting criteria values.

This main research question of this paper is: Can the set of reasonably applicable structural analysis criteria be reduced due to the kind of system (product, process, and organisation)? In this paper we focus on product models.

The paper is structured as follows. First, we describe our research approach for the literature survey, the model analysis and the correlation analysis (section 2). We present an overview of the models used in this paper and classify them according to model type, data base and model size (section 3). We show correlations among structural analysis criteria and cluster these to identify classes of criteria which might be broken down on a single criterion (section 4). We discuss the results and derive questions for future research (section 5). Finally, we conclude this paper by proposing future research and supporting activities (section 6).

2. Correlation analysis of structural properties

2.1 Literature research for structural product models

First performed an literature research to create a collection of structural product models. The collection should cover a wide range in terms of the model type (e.g. physical vs. functional), model size and product type (e.g. purely mechanical vs. mechatronic). We researched 17 major (based on the 2010 ISI rating) journals and the volumes of the past ten years. Table 1 lists the journals. Some volumes were not available due to licencing and are listed in table 1. Five journals are from the area of engineering design, five from engineering management and seven from systems engineering. Decision science and operations management were omitted as this paper focuses on product models.

Table 1. Researched journals

Name	Area	ISSN	Years
Journal of Engineering Design	Engineering Design	0954-4828	2001-2011
Research in Engineering Design		0934-9839	2001-2011
Design Studies		0142-694X	2001-2011
Concurrent Engineering-Research and Applications		1063-293X	2001-2011
Journal of Mechanical Design		1050-0472	2001-2011
Management Science	Engineering Management	0025-1909	2001-2009
Journal of Product Innovation Management		0737-6782	2001-2010
IEEE Transactions on Engineering Management		0018-9391	2001-2011
Journal of Engineering and Technology Management		0923-4748	2001-2002
Journal of Management in Engineering		0742-597X	2001-2011
IEEE Transactions on Systems Man and Cybernetics Part A	Systems Engineering	1083-4427	2001-2011
IEEE Transactions on Systems Man and Cybernetics Part B		1083-4419	2001-2011
IEEE Transactions on Systems Man and Cybernetics Part C		1094-6977	2001-2011
International Journal of System Science		0020-7721	2001-2010
IEEE Systems Journal		1932-8184	2001-2011
Systems Engineering		1098-1241	2001-2011
Journal of Systems Science and Systems Engineering		1004-3756	2001-2011

We found about 100 papers providing models of systems structures. These papers were reduced to papers which provide models fulfilling following criteria:

- Models describe a physical product
- Models are intended to be used in product design and development
- Models are fully available and not anonymized
- Models describe components and their interrelations
- Models describe undirected relations

By doing so we found 20 models. To supplement the collection we added models which are available in our research group. Finally, the collection comprises 35 models which are listed in table 5. Table 4 shows the sources of the models. The models were extracted from the papers and transformed into a text-based, computable matrix format.

2.2 Structural analysis of structural product models

Next we computed the structural criteria. The set of criteria is based on the work of [Maurer 2007] and [Kreimeyer 2010] and covers the available range of structural analyses. Then the models were analysed using LOOMEO™ 2.5.0. The computed metrics are shown in table 2 (global metrics characterizing complete structures) and in table 3 (local metrics characterizing nodes). The computations resulted in 36 text files: one file listing all models and the corresponding global metric values and 35 files each listing the nodes of one model and the corresponding local metric values.

Table 2. Global structural metrics

ID	Metric	Description
G01	Average clustering coefficient	Average relational density of node locality.
G02	Average degree	Ratio between number of edges and number of nodes.
G03	Average number of cliques per node	Average number of cliques per node.
G04	Average number of cliques per edge	Average number of cliques per edge.
G05	Number of cliques	Number of cluster which are internally fully connected.
G06	Average path length	Average of the distances between all pairs of nodes.
G07	Average distance centrality	Average minimum distance to each node.
G08	Number of edges	Number of edges.
G09	Average path centrality	Average percentage of shortest paths running across a node.
G10	Number of nodes	Number of nodes.
G11	Number of blocks	Number of clusters connected to other clusters via one node.
G12	Number of components	Number of clusters each pair of node indirectly connected.
G13	Average number of blocks per node	Average number of blocks per node.
G14	Average number of cycles per node	Average number of cycles per node.
G15	Average number of cycles per edge	Average number of cycles per edge.
G16	Number of cycles	Number of edge chains which form a loop.

2.3 Correlation analysis of structural analysis results

Next the dependencies among the criteria were identified using a correlation analysis. The dependencies are the basis for the grouping of the criteria. For each dataset (file) a correlation matrix of the metrics and the level of significance for each correlation was computed. Each matrix cell contains the Pearson coefficient of the two connected metrics. The level of significance was computed using the Student's t-test. The 35 correlation matrices of the node metrics were averaged. The levels of significance were combined using the minimum level for each correlation. All statistical analyses were done with Microsoft Excel™ 2010.

Table 3. Local node metrics

ID	Metric	Description
N01	Degree	Number of neighboring nodes.
N02	Path centrality	Percentage of shortest paths running across a node.
N03	Cycles per node	Number of cycles per node.
N04	Blocks per node	Number of blocks per node.
N05	Cliques per node	Number of cliques per node.
N06	Clustering coefficient	Relational density of node locality.
N07	Distance centrality	Minimum distance to each node.
N08	Average distance to node	Average distance to node.
N09	Maximum distance to node	Maximum distance to node.
N10	Median distance to node	Median distance to node.

Table 4. List of product model sources (* models not completely published but available on request from the authors of this paper)

ID	Source
S01	Ameri, F. et al., Research in Engineering Design, 19(2-3), 161-179, 2008
S02	Björnfot, A., Stehn, L., Journal of Engineering Design, 18(2), 113-124, 2007.
S03	Bonjour, E., Micaelli, J.-P. (2010). IEEE Transactions on Engineering Management, 57(2), 323-337, 2010.
S04*	Einögg, F., Netzwerk-FMEA: Methodik und Anwendung. Student thesis, Institute of Product Development, Technische Universität München, 2009.
S05	Hölttä-Otto, K., de Weck, O., Concurrent Engineering, 15(2), 113-126, 2007.
S06	Keller, R. et al., Journal of Engineering Design, 20(6), 571-587, 2009.
S07	Kreng, V., Lee, T.-P., Journal of Engineering Design, 15(3), 261-284, 2004.
S08*	Langer, S. et al., 11th International Design Conference DESIGN 2010, Dubrovnik: Design Society , 307–318, 2010.
S09	Lee, H. et al., Journal of Engineering Design, 21(1), 75-91, 2010.
S10	Lindemann, U. et al. Structural Complexity Management. Berlin: Springer 2009.
S11*	Maurer, M., Komplexitätsmanagement für die industrielle Praxis. Lecture transcript, Institute of Product Development, Technische Universität München 2011.
S12	Park, J., et al., Journal of Engineering Design, 19(6), 515-532, 2008.
S13*	Schmitz, S. et al., 11th International Design Conference on Engineering Design ICED 2011, Copenhagen: Design Society 2011.
S14	Smaling, R., Weck, O. D., Systems Engineering, 10(1), 1-25, 2006.
S15*	Strelkow, B., Strukturmodellierung und Strukturanalyse zur Bestimmung der Anpassungsfähigkeit einer Produktionsanlage. Student thesis, Institute of Product Development, Technische Universität München, 2010.
S16*	Teseon GmbH (2011). Example delivered with LOOMEO™ 2.5.0.

2.4 Clustering of correlation matrices

Last, the groups of the metrics were determined based on the dependencies among the criteria. For each group on criterion was determined which can represent the group as it is highly correlated to the other group criteria. The correlation matrix of the global metrics and the average matrix of the local metrics were clustered to highlight sets of highly correlated metrics. The clustering was done manually due to the small matrix sizes (16 by 16 and 10 by 10). The resulting matrices are shown in section 4. Figure 2 shows the correlation matrix of the global metrics. Figure 3 shows the averaged correlation matrix of the local metrics.

3. Overview of product models

In the literature review we found 35 models which describe 23 products. Table 5 shows the models with additional data like the relationship type, the way of data acquisition, the reference, the number of nodes and the number of edges. Table 4 shows all references for the models. The models from the references S04, S08, S11, S13, S15 and S16 are not publicly available as they:

- have not been published so far (S04 and S15)
- are part of course work (S11)
- show not all available data (S08, S13)
- are part of a software release (S16)

Table 5. List of product models

ID	System	Model	Data acquisition	Source	Nodes	Edges
P01	Spreader	Geometry	Work on system	S01	19	31
P02	Sprinkler	Geometry	Work on system	S01	21	29
P03	Timber structure	Geometry	Workshop/interview	S02	14	15
P04	Tied rafter	Geometry	Workshop/interview	S02	8	10
P05	Automatic gearbox	Product	Workshop/interview	S03	8	12
P06	Vacuum cleaner	Contact	Work on system	S13	30	44
P07	Vacuum cleaner	Contact	Work on system	S13	30	46
P08	Vacuum cleaner	Contact	Work on system	S13	30	53
P09	Vacuum cleaner	Contact	Work on system	S13	30	55
P10	Vacuum cleaner	Contact	Work on system	S13	30	49
P11	Vacuum cleaner	Contact	Work on system	S13	30	57
P12	Vacuum cleaner	Contact	Work on system	S13	30	49
P13	Vacuum cleaner	Contact	Work on system	S13	30	58
P14	Chain saw	Contact	Work on system	S04	18	30
P15	Cell phone	Function	Work on system	S05	11	16
P16	Desktop computer	Function	Work on system	S05	23	38
P17	Desk phone	Function	Work on system	S05	14	20
P18	Laptop computer	Function	Work on system	S05	16	22
P19	Diesel engine	Flow	Workshop/interview	S06	21	24
P20	Diesel engine	Geometry	Workshop/interview	S06	21	35
P21	Vacuum cleaner	Function	n/a	S07	34	75
P22	Vacuum cleaner	Contact	n/a	S07	34	76
P23	Automobile	Product	n/a	S09	17	37
P24	Diesel engine	Product	n/a	S16	28	65
P25	Assembly cell	Flow	Work on system	S15	110	70
P26	Assembly cell	Contact	Work on system	S15	110	147
P27	Electric razor	Product	n/a	S12	9	12
P28	Combustion engine	Flow	n/a	S14	32	45
P29	Combustion engine	Flow	n/a	S14	32	20
P30	Combustion engine	Flow	n/a	S14	32	23
P31	Combustion engine	Contact	n/a	S14	32	60
P32	Automobile	Geometry	Workshop/interview	S08	11	35
P33	Ball-pen	Contact	Work on system	S11	8	11
P34	Aircraft engine	Contact	n/a	S11	7	10
P35	Ball-pen	Contact	Work on system	S10	8	9

To classify the relationship type we follow the proposition by [Pimmler and Eppinger 1994]:

- Product (4 models): no specification beyond component structure of a product
- Geometry (8 models): geometric links such as contact or design space intersection
- Contact (13 models): specific geometric link – the components are in contact
- Flow (5 models): flows between the components such as energy, information or heat
- Function (5 models): relations linked to the overall system functionality

The classification scheme for data acquisition was newly created for this paper. We distinguish three ways (the list is by no means complete; other ways such as questionnaires and data mining were not used the references)

- Work on product (19 models): the modeller has access to product and can disassemble it
- Interview/workshop (6 models): the modeller interviews product experts to create the model
- n/a (10 models): the reference does not state the mode of the data acquisition

The models span a wide range of models sizes. The number of nodes runs from 7 to 110 with an average around 30. The number of edges runs from 9 to 147 with an average around 40. The type of systems varies from purely mechanical products such as ball-pens and sprinklers to highly integrated mechatronic products such as cell phones or assembly cells. Thus, the models cover a wide range of products and model types; they form a good base for our research.

4. Correlation matrices of structural properties

Sections 2.2. to 2.4. describe the creation of the clustered correlation matrices which are shown in figure 2 and figure 3. We omit the intermediate results for the sake of brevity.

4.1 Global structural properties

Figure 2 shows the clustered correlation matrix of the global metrics. The matrix contains 13 significant ($p < 0.05$), 6 very significant ($p < 0.01$) and 28 highly significant ($p < 0.001$) correlations. There are four clusters in the matrix: CG1 (metrics G01 to G05), CG2 (metrics G06 to G12), CG3 (metrics G13) and CG4 (metrics G14 to G16).

The cluster CG1 contains five metrics: average clustering coefficient (G01), average degree (G02), average number of cliques per node (G03), average number of cliques per edge (G04) and number of cliques (G05). The dependencies within the cluster are highly significant with two exceptions. The metric G03 (Average number of cliques per node) has the highest correlations to the other metrics (ranging from 0.58 to 0.98). Thus, it is a candidate for representing the complete cluster.

The cluster CG2 contains seven metrics: average path length (G06), average distance centrality (G07), number of edges (G08), average path centrality (G09), number of nodes (G10), number of blocks (G11) and number of components (G12). 14 dependencies within the cluster are highly significant; two dependencies are significant a and five dependencies are not significant. Thus the cluster is not as clear cut as CG1 and requires careful treatment. The metric G08 (Number of edges) has the highest correlations to the other metrics (ranging from 0.25 to 0.95). Thus, it is a candidate for representing the complete cluster. As the cluster is not completely significant other metrics have to supplement G08. The prime candidate is G12 (number of components) due to its highly significant correlations to the rest of the cluster.

The cluster CG3 contains only the metric G13 (Average number of blocks per node) which can represent itself and the cluster.

The cluster CG1 contains three metrics: average number of cycles per node (G14), average number of cycles per edge (G15) and number of cycles (G16). The dependencies within the cluster are highly significant with two exceptions. The metric G15 (average number of cycles per edge) has the highest correlations to the other metrics (ranging from 1.00 to 1.00). Thus, it is a candidate for representing the complete cluster.

4.2 Structural properties of nodes

Figure 3 shows the clustered correlation matrix of the global metrics. The matrix contains only two very significant ($p < 0.01$) correlations: between N01 (degree) and N03 (cycles per node) and between N08 (average distance to node) and N10 (median distance to node) . This can be explained by two observations. First, only the minimum level in all 35 datasets is used. Second, most of the small (number of nodes ≤ 15) models do not contain enough results to reach high levels of significance. We suggest to recompute the matrix using only models with 16 or more nodes. There are four clusters in the matrix: CN1 (metrics N01 to N05), CN2 (metrics N06), CN3 (metrics N07) and CN4 (metrics N08 to N10). All show high correlations.

The cluster CN1 contains five metrics: degree (N01), path centrality (N02), cycles per node (N03), blocks per node (N04) and cliques per node (N05). The metric N01 (degree) has the highest correlations to the other metrics (ranging from 0.63 to 0.84). Thus, it is a candidate for representing the complete cluster.

The cluster CN2 contains only the metric N06 (clustering coefficient) which can represent itself and the cluster.

The cluster CN3 contains only the metric N07 (distance centrality) which can represent itself and the cluster.

The cluster CN4 contains three metrics: average distance to node (N08), maximum distance to node (N09) and median distance to node (N10). The metric N08 (average distance to node) has the highest correlations to the other metrics (ranging from 0.86 to 0.91). Thus, it is a candidate for representing the complete cluster.

		CG1					CG2							CG3	CG4		
		G01	G02	G03	G04	G05	G06	G07	G08	G09	G10	G11	G12	G13	G14	G15	G16
CG1	G01		0.74***	0.83***	0.85***	0.41*	0.09	0.12	0.02	-0.26	-0.36*	-0.47**	-0.47**	-0.03	0.01	0.01	0.06
	G02	0.74***		0.93***	0.89***	0.60***	0.14	0.37*	0.28	-0.16	-0.22	-0.47**	-0.46**	-0.34*	0.35*	0.35*	0.47**
	G03	0.83***	0.93***		0.98***	0.58***	0.03	0.27	0.21	-0.21	-0.22	-0.41*	-0.36*	-0.27	0.23	0.23	0.33
	G04	0.85***	0.89***	0.98***		0.47**	-0.02	0.17	0.13	-0.22	-0.26	-0.40*	-0.35*	-0.18	0.12	0.12	0.21
	G05	0.41*	0.60***	0.58***	0.47**		0.59***	0.86***	0.78***	0.40*	0.36*	0.09	-0.17	-0.10	0.29	0.3	0.32
CG2	G06	0.09	0.14	0.03	-0.02	0.59***		0.71***	0.59***	0.60***	0.34*	0.21	-0.27	0.33	0.00	0.01	0.00
	G07	0.12	0.37*	0.27	0.17	0.86***	0.71***		0.95***	0.71***	0.63***	0.39*	-0.03	-0.02	0.24	0.25	0.27
	G08	0.02	0.28	0.21	0.13	0.78***	0.59***	0.95***		0.8***	0.81***	0.58***	0.25	-0.15	0.23	0.24	0.26
	G09	-0.26	-0.16	-0.21	-0.22	0.40*	0.6***	0.71***	0.8***		0.85***	0.81***	0.33	0.10	-0.06	-0.06	-0.07
	G10	-0.36*	-0.22	-0.22	-0.26	0.36*	0.34*	0.63***	0.81***	0.85***		0.92***	0.72***	-0.14	0.02	0.03	0.03
	G11	-0.47**	-0.47**	-0.41*	-0.40*	0.09	0.21	0.39*	0.58***	0.81***	0.92***		0.77***	0.09	-0.13	-0.13	-0.13
	G12	-0.47**	-0.46**	-0.36*	-0.35*	-0.17	-0.27	-0.03	0.25	0.33	0.72***	0.77***		-0.29	-0.06	-0.06	-0.07
CG3	G13	-0.03	-0.34*	-0.27	-0.18	-0.10	0.33	-0.02	-0.15	0.10	-0.14	0.09	-0.29		-0.21	-0.21	-0.23
CG4	G14	0.01	0.35*	0.23	0.12	0.29	0.00	0.24	0.23	-0.06	0.02	-0.13	-0.06	-0.21		1.00***	0.99***
	G15	0.01	0.35*	0.23	0.12	0.30	0.01	0.25	0.24	-0.06	0.03	-0.13	-0.06	-0.21	1.00***		1.00***
	G16	0.06	0.47**	0.33	0.21	0.32	0.00	0.27	0.26	-0.07	0.03	-0.13	-0.07	-0.23	0.99***	1.00***	

Figure 2. clustered correlation matrix of the global structural properties (level of significance: * p<0.05, ** p<0.01, *** p<0.001)

		CN1					CN2	CN3	CN4		
		N01	N02	N03	N04	N05	N06	N07	N08	N09	N10
CN1	N01		0.80	0.84**	0.63	0.83	-0.04	0.12	-0.08	-0.02	-0.10
	N02	0.80		0.52	0.8	0.55	-0.25	0.15	-0.14	-0.09	-0.14
	N03	0.84**	0.52		0.34	0.71	0.05	0.09	-0.05	0.00	-0.07
	N04	0.63	0.80	0.34		0.39	-0.18	0.06	-0.05	-0.03	-0.07
	N05	0.83	0.55	0.71	0.39		0.21	0.09	-0.07	-0.01	-0.07
CN2	N06	-0.04	-0.25	0.05	-0.18	0.21		-0.09	0.11	0.09	0.13
CN3	N07	0.12	0.15	0.09	0.06	0.09	-0.09		-0.49	-0.31	-0.44
CN4	N08	-0.08	-0.14	-0.05	-0.05	-0.07	0.11	-0.49		0.86	0.91**
	N09	-0.02	-0.09	0.00	-0.03	-0.01	0.09	-0.31	0.86		0.74
	N10	-0.10	-0.14	-0.07	-0.07	-0.07	0.13	-0.44	0.91**	0.74	

Figure 3. clustered averaged correlation matrix of the global structural properties (significance: * p<0.05, ** p<0.01, *** p<0.001)

5. Findings for selecting analysis criteria

Section 4 shows that structural properties are highly correlated and that the global metrics are highly significantly correlated. The properties form highly correlated clusters. For each cluster candidates for representing the whole cluster are given. Based on these observations we assume that the set of sensibly applicable structural analysis criteria can be reduced based on the type of system.

The results suggest that whole product structured can be characterized by a set of four criteria. The set should be sufficient to gain an overview of the structure and to gain some fundamental insights. As some of the candidates are hard to determine or seem not sufficient we also suggest alternatives and supplements. These criteria are:

- Average number of cliques per node – alternative: average degree
- Number of edges – supplement: number of components
- Average number of blocks per node
- Average number of cycles per edge – alternative: number of cycles

The results suggest that node can be characterized by a set of four criteria. The set should be sufficient to gain an overview and some fundamental insights. However these findings must be confirmed by an additional analysis as the results are not significant. These criteria are:

- Degree
- Clustering coefficient
- Distance centrality
- Average distance to node

We recommend to use the reduced sets of criteria for future research. Thus, the effort for determining what can be deduced from structural models can be drastrically reduced.

6. Summary and future work

In this paper we showed that the set of sensibly applicable structural analysis criteria can be reduced based on the type of system. To do so we did a correlation analysis of 16 global metrics and 10 node metrics using 35 models of product structures. The models were collected in an extensive literature research. They span a wide range of products, relationship types and data acquisition approaches.

We find that global insights into a structure can be gained by only four or five metrics. A similar reduction can be achieved for node metrics where only four metrics suffice. This result is one step to reach the overall aim of this research: to make structural more goal-oriented, efficient and meaningful. By reducing the number of sensibly applicable criteria structural analysis becomes more efficient both in research and in application. Thus future research can focus on a few metrics to determine what can reasonably be deduced from them.

Based on the available data additional analyses are possible. More metrics can be applied and tested against the existing analysis. However, we assume to have covered the major structural characteristics. Following research questions are potentially answerable based the available data:

- Does the type of relationship (e.g. geometry, contact, flow or function) influence the results of structural analysis?
- Does the way of data acquisition (e.g. work on system, workshop or interview) influence the results of structural analysis?

Future work has to confirm our findings e.g. by extending the data base. One possibility is the upcoming book [Eppinger and Browning 2012] which presents several models so far only partly published. Another initiative is run by the Special Interest Group Managing Structural Complexity. It aims creating a model repository for complex structures.

Our analysis should be repeated for other major types of systems such as parameter networks, organisation structures and process structures.

Acknowledgements

This research was made possible through the generous funding by the German Research Foundation (DFG) in the context of project A2 (“Modelling and analysis of discipline-spanning structural criteria and their impacts on product development processes”) within the Collaborative Research Centre SFB 768 (“Managing cycles in innovation processes”).

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