INTERNATIONAL DESIGN CONFERENCE – DESIGN 2022
https://doi.org/10.1017/pds.2022.76

Prototyping through the Lens of Network Analysis and Visualisation

L. Kent ✉, J. Gopsill, L. Giunta, M. Goudswaard, C. Snider and B. Hicks
University of Bristol, United Kingdom
✉ lee.kent@bristol.ac.uk

Abstract
Prototyping is a well-established and valued design process activity. However, capturing prototypes and the tacit knowledge that led to and was gained from their creation is a challenge. Beyond that, questions remain on how best to utilise that captured data. This paper looks at how one can exploit and generate insights from data that has been captured, specifically looking at graph databases, the network analysis techniques they permit and the differing fidelities of visualisation and interactivity that they enable.

Keywords: design process, network approaches, prototyping

1. Introduction

Prototyping is a well-established design activity spanning the physical and digital domains (Camburn, et al., 2015). Physical prototypes (Figure 1) bring tangibility to an idea or concept and are unambiguous representations, providing insights into perception and interaction. It also supports validation of a design's function and/or performance (Liker & Pereira, 2018). A virtual prototype is a digital mock-up, model or simulation of a physical object or phenomena (Wang, 2002), taking advantage of computing to perform complex calculations quickly and repeatably. Mixed Reality (MR) prototyping field seeks to achieve a 'best-of-both', combining both digital and physical media (Kent, 2021). However, questions remain in the appropriate application and combination of prototyping activities and whether we have maximised the potential knowledge that can be gained (Jensen, et al., 2016; Erichsen, et al., 2021).

The advantages and disadvantages of prototyping techniques often result in and/or necessitates a mixed prototyping approach to design. However, this leads to challenges in capturing information and rationale regarding the activities and synthesising what happened, e.g. when did it happen and by whom, and ultimately identifying the points where decisions were made that led to the final design. In many cases, the knowledge is tacit and contained within the engineers who have performed the activity.

In recent years, studies have investigated how one can capture early-stage prototyping activities and how the results of one prototyping activity have informed subsequent activities (Erichsen, et al., 2021; Giunta, et al., 2022), resulting in networks of connected activities. Other works have begun to identify the key knowledge elements that one should capture during a prototyping activity and their relationship with the prototyping media used (Real, et al., 2021). The work to date has highlighted the necessity of capturing the relationships between prototyping activities and their interconnections and fed back into the design process. While tools have been developed and tested in capturing the design rationale for a project's prototyping activities (Erichsen, et al., 2021; Giunta, et al., 2022), a question remains on the utility of the data collected and how it can be exploited for both design research and design practice.

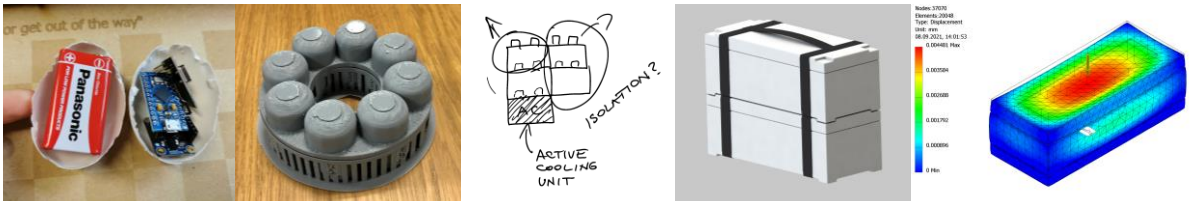


Figure 1. The diverse world of prototyping.

The contribution of this paper is in exploring how one can exploit and generate insights from prototyping relationship data using graph analysis and visualisation. These insights may take the form of identifying key prototypes or learnings that significantly influenced the direction of a project, a team's working dynamics or identify gaps in a prototyping process. The insights could then be used to support, for example, communicating key decision points in design reviews or the onboarding of new designers.

To start, the paper discusses the state-of-the-art in the capture of prototyping activities and how network analysis has already been applied to help our understanding of the design process (Section 2). This is followed by the methodology to explore applying network analysis to a prototyping design rationale dataset (Section 3). The results are presented, and a discussion ensues as to the merit of network analysis in developing insights from prototyping activity data and elicitation of further research questions and future work (Section 4). The paper concludes with the findings (Section 5).

2. Related Work

Capturing knowledge from the design process is a well-developed field with numerous examples and methods developed by the community (Goldschmidt, 2016; Wynn & Clarkson, 2018). Formulations, such as a design ontology for design knowledge exchange and management (Štorga, et al., 2010), and requirements for supporting engineering design communication (Gopsill, et al., 2013) formalise how to capture events in the design process such that it can be re-used and analysed in the future. Methods such as retrospective compilation following interviews (Lauff, et al., 2018) or logbook investigation (McAlpine, et al., 2017) alongside tools such as work sampling, Design Rationale eDitor (DReD), PartBook, and Lessons Learned methodologies have all been developed to capture portions of the design process (Skec, et al., 2015; Bracewell, et al., 2008; Gopsill, et al., 2015).

2.1. Knowledge from the Prototyping Process

Capturing knowledge from the prototyping process has also been researched. There are a large number of process models for capturing the design process (Wynn & Clarkson, 2018; Chandrasegaran, et al., 2013), but recently, researchers have developed lightweight web app-based tools to specifically capture prototyping activities (Nelson, et al., 2019; Erichsen, et al., 2021) using images and qualitative data. Embedded within these tools are the schemas that manage what is captured and how it is to be stored.

As the capture of prototyping activity has evolved and improved, the prominence and importance of the relationships between the prototyping activities, people involved, and the design projects they pertain to have risen. This has led to researchers asking how we can maximise the insights generated from these relational datasets, with Erichsen, et al., (2021) demonstrating the potential for visualisations of the network to provide insights into the design process. (Figure 2) shows the manually post-processed network of a single project, used to demonstrate the routes taken to reach the final concept.

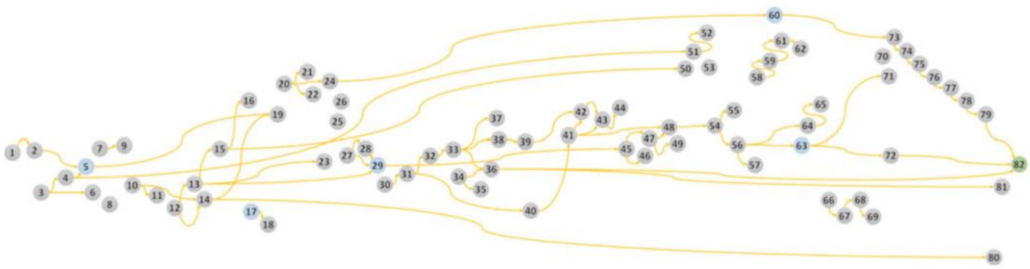


Figure 2. Prototyping activity network manually captured from data (Erichsen, et al., 2021)

https://doi.org/10.1017/pds.2022.76 Published online by Cambridge University Press

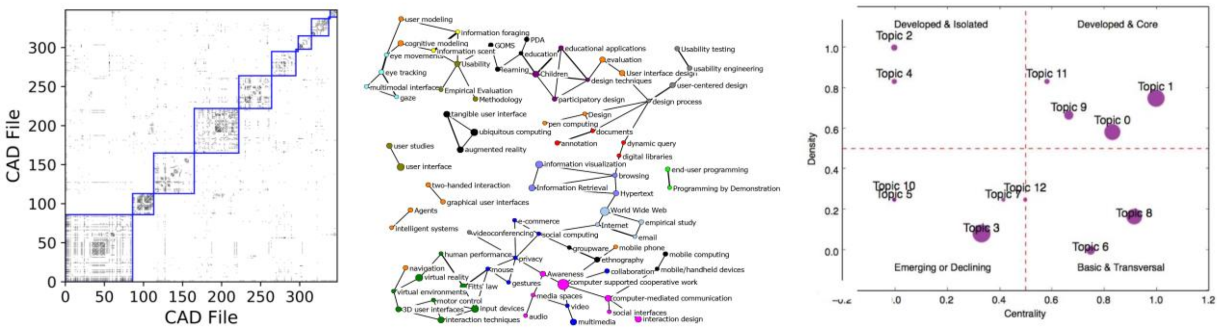
2.2. Network Analysis applied to the design process

Network analysis is a mature and well-developed field with numerous techniques to provide insights into network data structures, and it is no surprise that it has been used actively by the design community to examine the design process. In fact, the multi-disciplinary field of Design Structure Matrices (DSM), which evaluates the dependencies within our products and projects, is evidence of how successful and important this type of analysis is to design. Networks have been used to represent and analyse the design process through document evolution (Piccolo, et al., 2017), activities networks (Braha & Bar-Yam, 2007), information seeking activities (Cash, et al., 2013), and email (Parraguez Ruiz & Maier, 2016; Štorga, et al., 2013), but none explicitly use the prototypes that are generated through a design to create insights and support reflection on the design process.

Network analysis techniques have enabled us to predict the propagation of change through our product architectures (Clarkson, et al., 2004), and metrics, such as Modularity, provide a means to assess how well a graph can be clustered into sub-graphs representing modules and interfaces in a product (Gopsill, et al., 2019). Design teams can use this to reflect on their own teams' structures and align people to the emergent interfaces across their product architecture. Clustering techniques in combination with co-word network analysis has also been used to successfully identify emergent knowledge topics within R&D organisations (Gopsill, et al., 2020).

2.3. Network Visualisation of a design process through its prototypes

Visualisation plays a significant role in the planning, enacting and interpretation of a design process (Bresciani, 2019), and there are a range of representations suitable to represent different aspects of the design process (Idrissov, et al., 2020; Chandrasegaran, et al., 2013). Network visualisation can be used to aggregate and visualise the relationships between the elements of a system (in our case, the elements of a design process) into more manageable forms for human interpretation and decision making. A number of 2D visualisation techniques have been employed and include: re-arranged matrices in relation to the partitioning of terms; force-based network diagrams to reveal the connected nature of the terms; and, strategic diagrams that show the movement of topics over time (Figure 3). Extending visualisation into 3D has also been explored (Millais, et al., 2018; Anderson, et al., 2019), comparing modes and fidelities of inputs and interfaces, reporting that this increases data comprehension, but this comprehension is influenced by the novelty of the interface and the input device used.



(a) Matrix view (From: Gopsill et al. 2016)

(b) Network diagram (From: Liu et al. 2014)

(c) Strategic diagram (From: Jones et al. 2015)

Figure 3. Graph visualisations

Given the prominence of networks and the need to capture the links between prototypes, it is logical to suggest that network analysis of prototyping process data will give valuable insights into the process and, ultimately, the design. There are currently few examples of this (Fonnet & Prie, 2021). This paper will use a pre-existent network graph (Giunta, et al., 2022) and typical network analysis techniques and visualisations to attempt to draw insights from the design process that was followed. This should include peripheral and tacit information, such as team dynamics and key or influential prototypes. Extending the visualisation capability into 3D, and what new information this permits will also be explored. The results are subsequently presented with the author's providing their own interpretation as to the insights each of

https://doi.org/10.1017/pds.2022.76 Published online by Cambridge University Press

the analytical techniques brings to our understanding of prototyping - both from a design research and design practice perspective.

3. Methodology

The dataset to be used was captured using Pro2booth (Giunta, et al., 2022) as part of the International Design Engineering Annual challenge, a design competition involving labs from the Engineering Design academic community (Goudswaard, et al., 2022). The Pro2booth platform and network schema is described fully by Giunta, et al., (2022), and has two types of nodes, prototypes, and designers. Four teams of designers worked to solve an engineering challenge, documenting their progress through prototype captures using the Pro2booth platform. This provided a rich dataset of 204 prototypes that demonstrate the teams' journeys through the design process. (Table 1) provides an overview of the dataset.

Table 1. The IDEA dataset, captured with Pro2booth.

Category	Teams	Designers	Prototypes	Edges (Created by)	Edges (Influenced By)
Count	4	14	204	373	994

3.1. Analysis

The dataset was post-processed and formatted into a graph format that the Python NetworkX package could load and manipulate. NetworkX affords a number of network analysis and visualisation techniques. In this case, it was used to create sub-graphs of the individual team's prototyping process where details such as the number of prototypes and individuals involved (i.e., nodes) and which prototype influenced which other prototype, as well as the individuals involved (i.e., edges), could be queried and reported. In addition, four centrality measures were applied:

- *Degree:* a count of the number of prototypes a prototype references or has been referenced by.
- *Eigenvector:* a measure of the influence of a prototype, with a prototype scoring highly by being connected to prototypes that are equally well connected.
- *Closeness:* an indication of how easy it is to traverse the network from one node to another.
- *Betweenness:* scores nodes highly if they consistently fall on the shortest paths between nodes.

Another common analysis to perform on a graph is how well the data groups up into smaller sub-graphs and is often an indication of how modular the process has been and the nature of the interfaces between elements of work, this is referred to as:

- *Clustering:* here the authors have applied Newman-Girvan's algorithm (NetworkX, 2022) to find a set of sub-graphs that provides an optimal Modularity score.

3.2. Visualisation

NetworkX was used to plot 2D figures of the network using a spring layout algorithm with different colours and labels denoting the prototype and individual nodes. The spring layout 'relaxes' the network, with more connected nodes being at the centre, and fewer or unconnected nodes pushed to the extent of the chart. As a result, the network can be explored visually. Two visualisations are created:

- *Prototypes and designers*: a spring layout visualisation of prototype and designers nodes, showing prototypes in relation to those who created them.
- *Prototypes:* a spring layout visualisation of just the prototypes and the influences between them

Deploying the data into a 3D environment gives us a new method of interacting with the network, with the capability of exploration giving breadth to the analysis. The advantage here is that there are multiple new and dynamic ways to present the data, (Millais, et al., 2018), something with few examples in design studies (Fonnet & Prie, 2021). The study presented here explores this via two implementations:

- *Design sphere:* plots prototypes randomly at the bounds of a sphere, with influences visualised and filtering by team possible. The sphere can be regenerated with a button press, and specific prototype information can be found by hovering the mouse over the node.

https://doi.org/10.1017/pds.2022.76 Published online by Cambridge University Press

- *Chronological influence network:* plots the prototypes in the order that they were created against their number of edges.

In this instance, the 3D visualisation of the network used the Unreal Engine to generate the network in an interactive 3D environment.

4. Results

The results are presented as network analysis and visualisation.

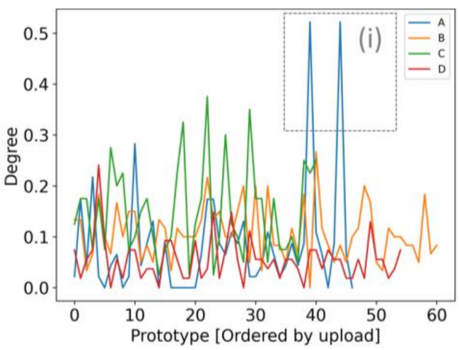
4.1. Network Analysis

(Table 2) summarises the four teams' prototyping process graphs. It can be seen that whilst the number of prototypes uploaded are not hugely different, the number of edges is. Furthermore, when considering the number of *created by* edges to the number of prototypes uploaded, it is clear that Projects A and B assigned more than one creator to most of their prototypes, with each prototype in Projects C and D typically only having one creator. The results alone could indicate the level of collaboration, mode of working and degrees of divergence or convergence in the design process.

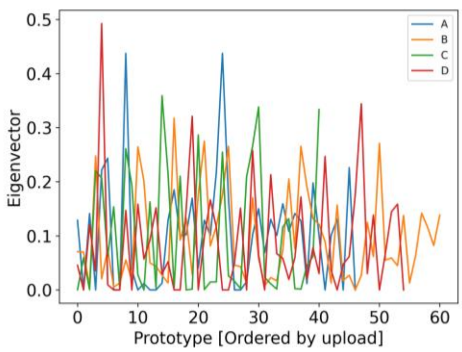
Table 2. Team network Statistics.

	Project / Team	A	B	C	D
Nodes	People	3	4	3	4
	Prototypes	47	61	41	55
Edges	Created By	134	134	45	60
	Influenced By	186	394	248	166

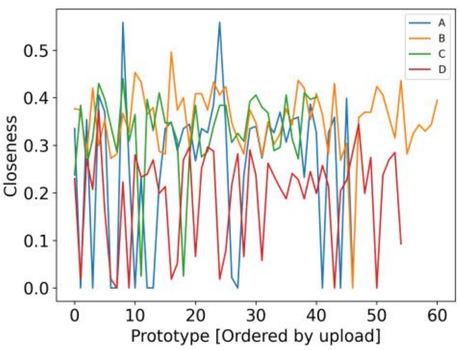
The analysis then continued into the generation of centrality measures for the prototypes in the graph. Centrality measures indicate the connectedness and inferred importance of a node to the network. Degree, Eigenvector, Closeness and Betweenness centralities for the four teams' prototyping processes and shown in (Figure 4 a-d), respectively. The prototypes have been ordered by their appearance in the design process.



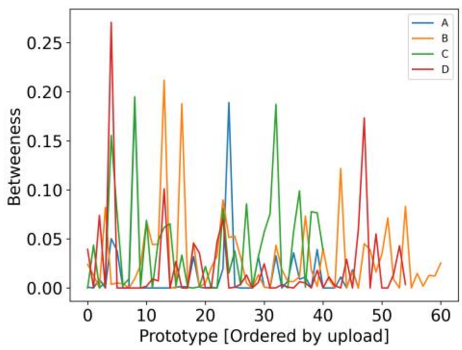
(a) Degree centrality



(b) Eigenvector centrality



(c) Closeness centrality



(d) Betweenness centrality

Figure 4. Network analysis using centrality measures

https://doi.org/10.1017/pds.2022.76 Published online by Cambridge University Press

Degree centrality: From (Figure 4a), we see Project A having the most connected prototypes near the end of their design process (Figure 4a-i) while B and C are more or less in the middle, with D featuring some highly connected prototypes early on, but overall, their prototypes are not as connected as the other three.
Eigenvector centrality: (Figure 4b) features a lot of noise, but there is a trend for the early prototypes to have a higher score than ones further down in the process, which is logical as they have existed longer in the network. It also highlights how those early prototypes subsequently drive the design process. Thus, it may be the case that design processes with highly influential prototypes early on shows a convergent design process.
Closeness centrality: (Figure 4c) is particularly noisy, due to a number of prototypes not existing as part of the main network. Of the connected nodes, the scores are similar, making it difficult to note any distinguishing features of their design process other than that they are consistent with one another.
Betweenness centrality: (Figure 4d) reveals that some prototypes score much higher than others and can be easily distinguished by the score. This suggests that these prototypes form the main bridges across the prototyping process and are highly influential; it is interesting to see them occurring at different stages for each of the four teams.
Clustering: (Figure 5) shows the results from the cluster analysis with the number of clusters and the score of how successfully the networks cluster - Modularity (0-1). All but Team A have reasonable Modularity scores of > 0.3, indicating a 'good' clustering (Newman, 2004). This suggests that Team B, C, and D's prototyping processes could be broken into smaller groups of activity while Team A features a single large activity with lots of minor activities. These could have been prototypes that attempted a new but failed feature. Team D scored the highest Modularity, with clusters featuring similar numbers of prototypes. This suggests that Team D evaluated concepts or design features to a similar level of fidelity and detail. In summary, the metric results present some compelling evidence in their ability to describe and/or identify differences in the prototyping processes of design teams.

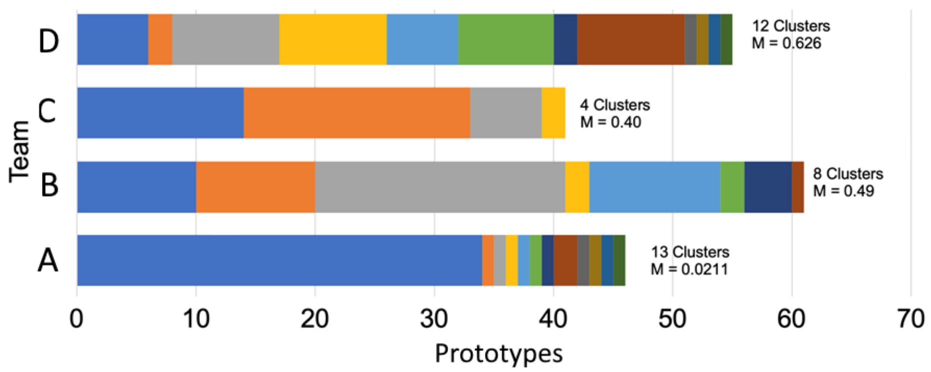
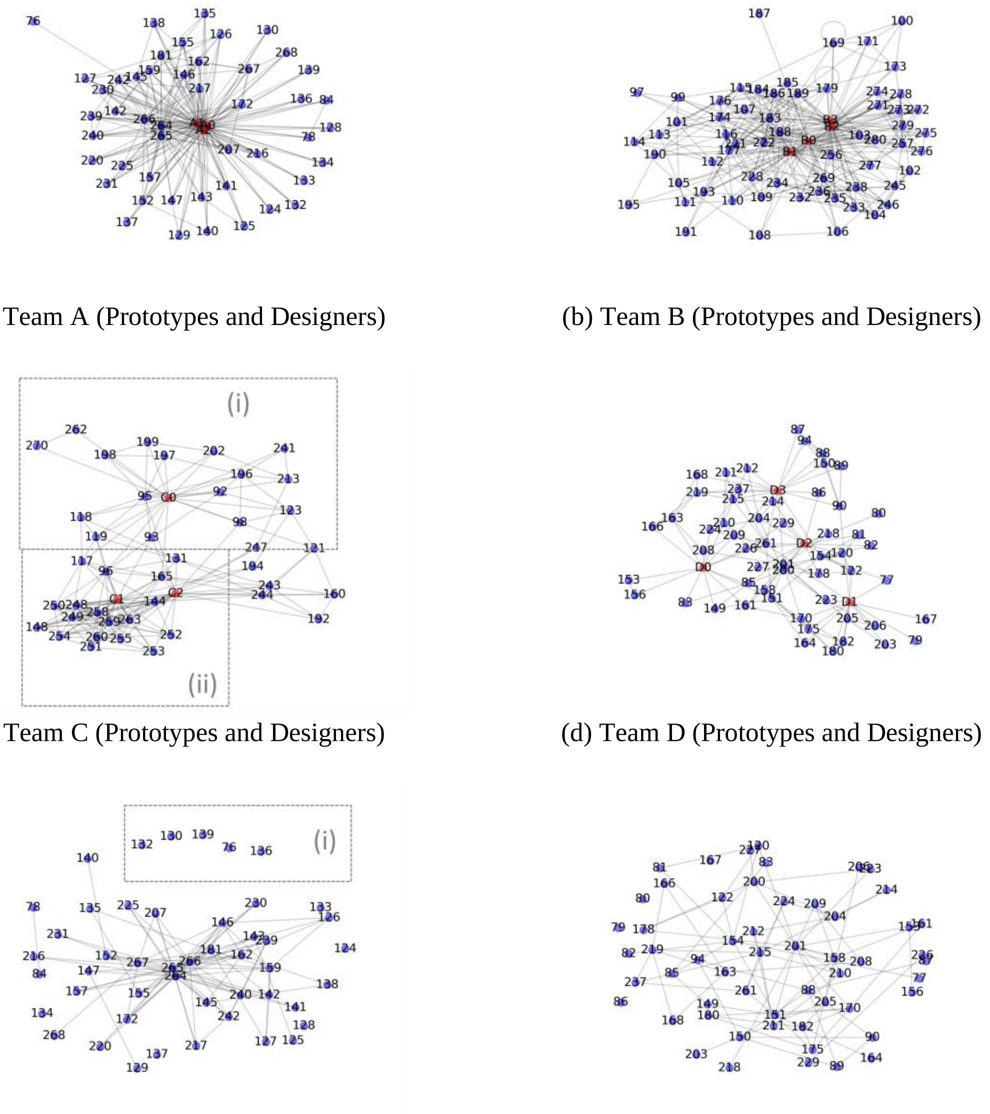


Figure 5. Clustering the prototyping process

4.2. Network Visualisation

Prototypes and Designers: (Figure 6a-f) 2D spring layout views of the network reveal several previously unknowable insights. From (Figure 6a and 6b), it can be seen that Team A and B's designers appear to have worked in close collaboration on all prototype (blue) nodes, as can be seen by clustering of the designer (red) nodes. Team C split into two teams working on different sub-systems, apparent in (Figure 6c) split roughly into the two groups with two of the designers (red nodes (Figure 6c-i)) being tightly paired and working on one set of prototypes. The third designer (Figure 6c-ii) may have worked on a range of more converging prototypes, with fewer edges linking the prototypes. Team D's graph (Figure 6d) implies that members assigned specific sub-systems or concepts to explore due to the lack of clustering.
Prototypes: Team A had several highly influential prototypes (Figure 6e), seen by the centralisation of several of the prototypes. Team A also has several prototypes that are disconnected, in that they were not influenced by and did not influence any other prototype (highlighted in Figure 6e-i). Team D had the fewest influences among their prototypes, with no evidence of key prototypes due to the uniform spread of data points in (Figure 6f). For brevity, Teams B and C prototype networks are omitted.

https://doi.org/10.1017/pds.2022.76 Published online by Cambridge University Press



(a) Team A (Prototypes and Designers)

(b) Team B (Prototypes and Designers)

(c) Team C (Prototypes and Designers)

(d) Team D (Prototypes and Designers)

(e) Team A (Prototypes)

(f) Team D (Prototypes)

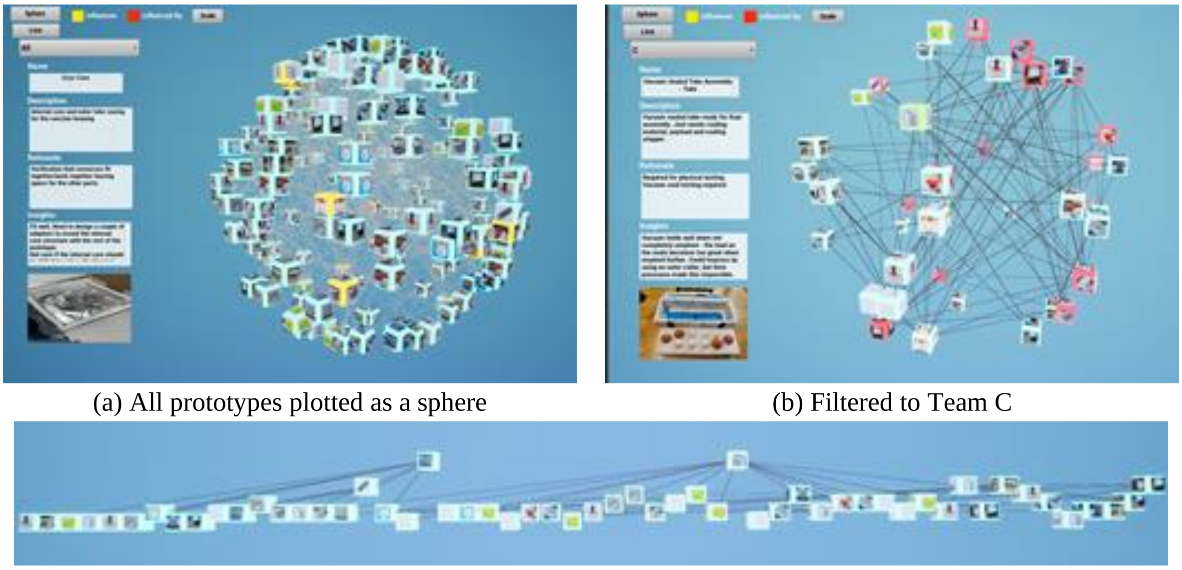
Figure 6. 2D network analysis

Design sphere: First, the entire dataset is plotted randomly at the bounds of a sphere with edges visualised, demonstrating the challenges with overplotting, (Figure 7a). (Figure 7b) shows the same sphere, but through a filter, in this case, Team C. There is still an element of over-plotting, as the 3D space does not lend itself to 2D images. However, these spheres can be redrawn at any scale, providing options for presenting and exploring the data. Specific prototyping information can also be found by selecting the prototype to be investigated, where previously a new query would have to be constructed.

Chronological influence network: We can identify the most influential prototypes in Team C's design process (Figure 7c). The first of the two has several previous prototypes that influenced it but did not influence future prototypes, indicating this was the endpoint of the specific line of thinking. This aligns with the design council double diamond (Design Council, 2022), indicating two stages of divergence and convergence. The influences between prototypes are also clear, and more influential prototypes can be scaled or placed more prominently in the visualisation. In this environment, the queries are embedded into the platform and linked to the interface for interrogation. Similar to visualisation depending on queries and metrics, immersion builds on those capabilities to add emerging value.

https://doi.org/10.1017/pds.2022.76 Published online by Cambridge University Press

What is not shown here is an extension of the data into the real world, using mixed reality. Here, data may be explored more organically and with more context exploration, such as seeing each prototype at the actual physical scale rather than just relative differences.



(a) All prototypes plotted as a sphere

(b) Filtered to Team C

(c) Team C prototypes ordered by upload with vertical position scaled by the number of edges

Figure 7. 3D network analysis

5. Discussion and Future Work

Charts exist to make data interpretation more straightforward, so it stands to reason that they are useful to capture and interpret the design process. So far, the potential of network analysis and visualisation to generate insights into the design process has been demonstrated. Many of the conclusions drawn, particularly from the visualisations, are subjective at this stage and have taken a surface-level analysis of the design process and patterns that emerged. The insights are open to both reinterpretation and argument, but the fact that insights have been drawn indicates potential value. Furthermore, visualisation and immersion in 2D and 3D may help discover unknown-unknowns (Jensen, et al., 2017), as the analyst does not need to create targeted and specific queries to obtain new insights; the insights can be found more organically.

By looking beyond the analysis and opting to visualise the data with interaction, human intuition can take the reins and direct the data exploration. The findings of the visualisation reinforce the findings of the analysis in a more tractable and intuitive manner. Four instances of collaborative working dynamics have been demonstrated, and a series of insights into team dynamics and influential clusters of prototypes can be identified. An inherent risk with moving to too complex visualisations is when there are too many or too few data points. Too few would mean that the graph and charts will be sparse, and it will be difficult to draw any meaningful conclusions. Too many could cause overplotting, such as can be seen in (Figure 7).

As the data has been localised in 3D space, the data can be extended into the real world, achievable through game engine functionality. There is work to determine the best methods and interfaces to get the most, if anything, out of this as part of the field of immersive analytics. VR, in particular, has been utilised to explore graphs and has led to fewer inaccurate insights being made compared to two-dimensional counterparts (Millais, et al., 2018). There are also challenges here with information overload. This is different to too much data in that the complexity of the interface is appropriate for the complexity of the task (Radkowski, et al., 2015).

The next steps are to triangulate the findings against the actual designers who generated the dataset. This will be achieved by inviting those designers in the project to reflect on and validate the insights, individually, as a team, and against the conclusions presented in this paper. These insights can also be explored and validated using different layouts in 2D and 3D. This will provide an opportunity to

https://doi.org/10.1017/pds.2022.76 Published online by Cambridge University Press

compare capability vs usability. We hypothesise that more complex and capable tools in 2D and 3D will permit more rich insight, but at the cost of usability, requiring more time to input information, disrupting the design process.
In this paper, only the connections between prototypes within the projects have been explored, but each prototype has embedded metadata, descriptions, rationale, and prototype specific insights that can be analysed. In the future, we also will explore if the data is interpreted in the same way and if different outputs act as a suitable intermediary or boundary object to facilitate discussion when reflecting on the process.

6. Conclusion

Prototyping is an inherently networked activity with previous prototypes influencing future prototype development and the direction of the design process. Recent advances in design rationale captures tools now enable us to capture the relationships between prototypes. In this paper, we have demonstrated the potential that network analysis and visualisation can bring to understanding the complex dynamics of prototyping.
The paper has shown that network analysis can provide insights into the key influencing prototypes and the convergent/divergent thinking that occurs through the design process via centrality measures. While clustering provides insights into the modular nature of prototyping. Network visualisation, on the other hand, facilitates greater discussion on the data enabling it to be open to interpretation. In this study, we show that insights on modes of working and key decisions points can be developed. Overall, the study reveals that network analysis and visualisation has and will continue to have a leading role to play in how we examine and interpret the design process.

Acknowledgements

The work reported in this paper was conducted at the University of Bristol in the Design and Manufacturing Futures Laboratory (www.dmf-lab.co.uk) as part of EPSRC grant ref: EP/R032696/1 on the Twinning of digital-physical models during prototyping project.

References

Anderson, B. J. H., David, A. T. & Weber, G., 2019. Immersion or Diversion: Does Virtual Reality Make Data Visualisation More Effective?. *International Conference on Electronics, Information, and Communication (ICEIC)*, pp. 1-7.

Bracewell, R., Wallace, K., Moss, M. & Knott, D., 2008. Capturing design rationale. *Computer-Aided Design*, 41(3), pp. 173-186.

Braha, D. & Bar-Yam, Y., 2007. The statistical mechanics of complex product development: Empirical and analytical results.. *Management Science*, 53(7), pp. 1127-1145.

Bresciani, S., 2019. Visual design thinking: a collaborative dimensions framework to profile visualisations. *Design Studies*, Volume 63, pp. 92-124.

Camburn, B. et al., 2015. A Systematic Method for Design Prototyping. *Journal of Mechanical Design*, 137(8), p. 081102.

Cash, P., Tino, S. & Mario, Š., 2013. An Analysis of Engineers Information Seeking Activity. s.l., IDETC/CIE.

Chandrasegaran, S. K. et al., 2013. The evolution, challenges, and future of knowledge representation in product design systems. *Computer-Aided Design*, 45(2), pp. 204-228.

Clarkson, J., Simons, C. & Eckert, C., 2004. Predicting change propagation in complex design. *Mechanical Design*, 126(5), pp. 788-797.

Design Council, 2022. What is the framework for innovation? Design Council's evolved Double Diamond. [Online] [Accessed 14 02 2022].

Erichsen, J., Sjöman, H., Steinert, M. & Welo, T., 2021. Protobooth: gathering and analyzing data on prototyping in early-stage engineering design projects by digitally capturing physical prototypes. *Journal of Artificial Intelligence in Engineering Design, Analysis and Manufacturing*, 35(1), pp. 65-80.

Fonnet, A. & Prie, Y., 2021. Survey of Immersive Analytics. *IEEE Transactions on Visualization and Computer Graphics*.

Giunta, L. et al., 2022. Pro2Booth: Towards an Improved Tool For Capturing Prototypes and the Prototyping Process. *International Design Conference*.

Goldschmidt, G., 2016. Linkographic Evidence for Concurrent Divergent and Convergent Thinking in Creative Design. *Creativity Research Journal*.
Gopsill, J., Humphrey, M., Thompson, D. & Garcia, E., 2020. *Co-word graphs for design and manufacture knowledge mapping*. Cavtat, Design Society.
Gopsill, J., McAlpine, H. & Hicks, B., 2013. A social media framework to support engineering design communication. *Advanced Engineering Informatics*, 27(4), pp. 580-597.
Gopsill, J., McAlpine, H. & Hicks, B., 2015. Supporting engineering design communication using a custom-built social media tool - PartBook. *Advanced Engineering Informatics*, 29(3), pp. 535-548.
Gopsill, J., Snider, C. & Hicks, B., 2019. The emergent structures in digital engineering work: what can we learn from dynamic DSMs of near-identical systems design projects?. *Design Science*, Volume 9.
Goudswaard, M. et al., 2022. *Pro2Booth*. Cavtat, s.n., p. [In Review].
Idrissov, A., Škec, S. & & Maier, A., 2020. Visualising Systems: Mapping System Features and Interactive Information Visualisations in Design. *International Design Conference*, pp. 2295-2304.
Jensen, L., Özkil, A. & Mortensen, N., 2016. *Prototypes in Engineering Design: Definitions and Strategies.* Cavtat, Proceedings of the DESIGN 2016 14th International Design Conference.
Jensen, M., Elverum, C. & M, S., 2017. Eliciting unknown unknowns with prototypes: Introducing prototrials and prototrial-driven cultures. *Design Studies*.
Kent, L., 2021. Mixed reality in design prototyping: A systematic review. *Design Studies*.
Lauff, C., Kotys-Schwartz, D. & Rentschler, M., 2018. What is a Prototype? What are the Roles of Prototypes in Companies?. *Journal of Mechanical Design*, 140(6), p. 061102.
Liker, J. & Pereira, R., 2018. Virtual and physical prototyping practices: finding the right fidelity starts with understanding the product. *IEEE Engineering Management Review*, 46(4), pp. 71-85.
McAlpine, H., Cash, P. & Hicks, B., 2017. The role of logbooks as mediators of engineering design work. *Design Studies*, Volume 48, pp. 1-29.
Millais, P., Jones, S. & Kelly, R., 2018. Exploring Data in Virtual Reality: Comparisons with 2D Data Visualizations. *CHI '18: CHI Conference on Human Factors in Computing Systems*.
Nelson, J., Berlin, A. & Menold, J., 2019. ARCHIE: An Automated Data Collection Method for Physical Prototyping Efforts in Authentic Design Situations. *ASME 2019 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*.
NetworkX, 2022. *Girvan-Newman algorithm.* [Online] Available at: https://networkx.guide/algorithms/community-detection/girvan-newman/[Accessed 17 02 2022].
Newman, M. E. J., 2004. Analysis of weighted networks. *Physical Review E*.
Parraguez Ruiz, P. & Maier, A., 2016. Using Network Science to Support Design Research: From Counting to Connecting. *Experimental Design Research*, pp. 153-175.
Piccolo, S., Lehmann, S. & Maier, A., 2017. *Using data- and network science to reveal iterations and phase-transitions in the design process.* Vancouver, Proceedings of the 21st International Conference on Engineering Design (ICED17).
Radkowski, R., Herrema, J. & J, O., 2015. Augmented Reality-Based Manual Assembly Support With Visual Features for Different Degrees of Difficulty. *International Journal of Human-Computer Interaction*.
Real, R., Snider, C., Goudswaard, M. & B, H., 2021. Dimensions of Knowledge in Prototyping: A Review and Characterisation of Prototyping Methods. *Proceedings of the Design Society*, Volume 1, pp. 1303-1312.
Skec, S., Štorga, M., Ribarić, Z. & Marjanovic, D., 2015. Work sampling approach for measuring intellectual capital elements in product development context. Milan, Design Society.
Štorga, M., Andreasen, M. & Marjanović, D., 2010. The design ontology: foundation for the design knolwedge exchange and management. *Journal for Engineering Design*, 21(4), pp. 427-454.
Štorga, M., Mostashari, A. & Stanković, a. T., 2013. Visualisation of the organisation knowledge structure evolution.. *Journal of Knowledge Management*.
Wang, G., 2002. *Definition and Review of Virtual Prototyping.* s.l., Journal of Computing and Information Science in Engineering.
Wynn, D. & Clarkson, P., 2018. Process models in design and development. *Research in Engineering Design*, Volume 29, p. 161–202.