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Student vs Machine: Comparing Artificial Neural Network Predictions with Student Estimates of Market Price Using Function Structure Models

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Abstract

This paper investigates the use of ANNs to model human behaviour in design by comparing the predictive capability of ANNs and engineering students. Function structure models of 15 products are used as input for prediction. The type of information provided varied between topology and vocabulary. Analysis of prediction accuracy showed that ANNs perform comparably to students. However, students are more precise with their predictions. Finally, limitations and future work are discussed, with research questions presented for subsequent research.

Keywords: artificial intelligence (AI), functional modelling, design education

1. Motivation: Predicting Future Performance in Early Design

The engineering design process provides designers with a systematic framework to solve problems from an engineering perspective (Dieter and Schmidt, 2013; Dym and Little, 2000; Pahl *et al.*, 2013; Ullman, 1992). Throughout the process, designers must make a series of decisions that ultimately translate to the success, quality, and efficiency of the solution. Many of these decisions are made using empirical evidence; however, some require designers to make a judgment based on their subject matter expertise, experience, and historical knowledge. While experts in their respective fields can make such decisions, novice designers may not possess the tools needed to confidently make such decisions. Alternatively, in situations where decisions are to be based on empirical evidence, time and resource limitations may restrict a comprehensive study or inquiry that will allow the designers to confidently make decisions. For instance, a design team may want to consult stakeholders about selecting between solution candidates or query end-users regarding preferences on non-functional requirements. In such cases, a simulation tool that can provide an estimate of stakeholder preferences and market prices based on historical data provides designers with an additional layer of confidence. While such a tool does not explicitly exist, modelling human behaviour in design and modelling consumer preferences are areas of ongoing research.

1.1. Modelling consumer preferences and design behaviour

Several research areas have investigated topics within the realm of modelling human behaviour, preferences, and values to support design decisions and design activities. Work has been done to understand the role of heterogeneity within the stakeholders on product preferences, where an ordered logit model was used to model consumer perception and evaluation of the product as a whole, as well as constitutive sub-systems (Hoyle *et al.*, 2011). Preference modelling has also been approached from an optimization perspective, where local utility functions are embedded into a multi-objective optimization problem which then identifies efficient solutions and flags inconsistencies in the model (Yang and Sen, 1996). Alternatively, utility functions have been augmented with a preference learning method to aid engineers in decision making (Wan and Krishnamurty, 2001). Other work on preference modelling uses fuzzy sets to model the subjectivity within design; an outranking preference model is used to provide support in concept selection (Wang, 2001). Similarly, an approach based on vector fields has been used to model the subjective preferences of customers such as the aesthetics of cars (Petiot and Grognet, 2006). A nested ANN-based approach has been used to model sound quality preferences, where the ANN tool was specifically developed to substitute data from a jury comprised of stakeholders (Pietila and Lim, 2015). A data-driven approach has also been investigated using product attribute data and online customer reviews to model customer choice (Suryadi and Kim, 2019).

Human behaviour in design, in terms of problem solving, has been studied using Markov chains and agent-based modelling (McComb *et al.*, 2017). Markov chains are used in this case to determine the complexity needed to accurately represent the sequencing behaviour exhibited by participants in solving a given problem. The patterns and probabilities captured in the Markov model are then used to deploy an agent-based model. Simulated teams are tasked with a truss design problem, and results show that the use of sequencing resulted in a significantly higher quality of designs. Human behaviour in truss design tasks has also been used to train a deep learning agent which performed comparably to humans (Raina *et al.*, 2019) In addition to modelling human behaviour and preferences, tools developed to support decision making for designers and engineers include the use of design heuristics (Lee *et al.*, 2017), and utility theory (Fernández *et al.*, 2001). While researchers have begun exploring the use of artificial intelligence and neural networks in modelling human behaviour in design activities, it is still growing field. The work presented in this paper compares human predictions with ANN predictions to investigate the feasibility of modelling human behaviour with ANNs in specific design tasks.

1.2. Prediction using artificial neural networks

Prediction using artificial neural networks (ANN) has been used in prior work to estimate the assembly time and market value of electro-mechanical products using assembly models and function structure models (Mathieson *et al.*, 2011; Sri Ram Mohinder et al., 2017; Sridhar *et al.*, 2016a). Additionally, neural networks have also been used to estimate assembly defects using an assembly model (Patel *et al.*, 2017), and to estimate life cycle assessment using project requirements (Visotsky *et al.*, 2017). The neural networks used in all of these cases are backpropagation networks designed with a cascade forward architecture, meaning each subsequent layer receives not only the outputs of the previous layer, but also the initial inputs given to the network. A high-level overview of the prediction procedure is shown in Figure 1.

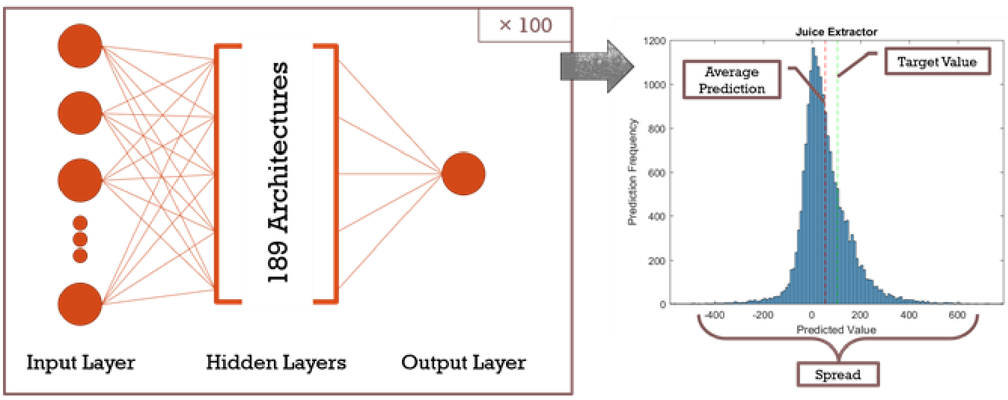

Figure 1. Overview of the ANN-based prediction procedure

The number of neurons in the hidden layers ranged from one to fifteen and up to three hidden layers were allowed, resulting in a total of 189 possible architectures. For example, the neural network may consist of only one neuron in a single hidden layer or be made up of three hidden layers with fifteen neurons distributed in a 7-5-3 sequence. These 189 architectures were then repeated 100 times each

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with randomly assigned initial weights, ultimately returning 18,900 market value predictions for a single product (Mathieson et al., 2011). It should be noted that out of the 189 structures, 15 networks will only have one hidden layer. As a result, the neural network-based prediction presented here is a mix of shallow and deep networks. Deep learning networks generally use raw unstructured data as input, while shallow networks need the data to be pre-processed to be effective (Lecun et al., 2015). Work presented in this study uses pre-processed data even in cases where multiple hidden layers are present in the network architecture. Although the effects of network depth on prediction are out of scope for this paper, it is an interesting question for future research.

1.3. Research questions

As a preliminary step in creating a simulation tool to help designers estimate customer preferences, it is important to understand how humans compare to artificial neural networks. Prior work has been done comparing humans with neural networks in the area of image recognition (Geirhos *et al.*, 2017) and sound quality preference (Pietila and Lim, 2015). More recently, researchers have compare humans with deep learning agents in truss design (Raina *et al.*, 2019). However, comparison of human and neural network performance in predicting late-stage design information is relatively unexplored. This work attempts to address that gap by investigating the following research questions.

- **RQ1**: How do ANNs compare to students for predicting the market value of electromechanical products using function structure models?
- **RQ2**: How does the type of information used for prediction affect prediction accuracy and precision?

The research questions are specific and targeted to allow for a preliminary comparison of student and machine predictions in a setting where both systems are similarly uninformed about the underlying physics. This allows for a comparison of the prediction systems without bias emerging from knowledge and experience.

An experiment was designed to address the research questions, where students were provided one of two versions of function structure models (type of information – RQ2) with associated market values. Following a review of the given information, student participants were asked to estimate the market value of new function structure models. Similarly, an experiment was conducted where a set of ANNs were trained, and market value predictions were generated from function structure models. These predictions were subsequently compared to student estimates (prediction capability – RQ1). A detailed description of the experiment design is provided in the following section.

2. Experiment Design

The primary goal of this experiment is to compare the predictive capability of ANNs to that of fourth-year mechanical engineering undergraduate students. In this case, function structure models are to be used to predict market values of household products (Gill *et al.*, 2017; Mathieson *et al.*, 2011; Sridhar *et al.*, 2016b). Function structure models for fifteen household products were collected from the design repository (https://design.engr.oregonstate.edu/repo) and associated costs for these products were calculated as an average of five different quotes (Mathieson *et al.*, 2011; Sri Ram Mohinder et al., 2017). The number of functions and flows present in the function structure models are shown in Table 1. Additionally, the average market values are also presented in the “Average MV” column.

As shown in Table 1, a majority of the function structure models have 15-30 functions and 20-40 flows, with some notable exceptions. For example, the Solar Yard Light only has six functions and nine flows, whereas the Sewing Machine has 44 functions and 63 flows. Similarly, the average market value of the products ranged from $2.89 to $214.95, however, most of the products were valued between $20 and $120. The products were then randomly divided into five groups for k-fold cross validation (Bengio and Grandvalet, 2004). These groups are denoted in Table 1 in the “G#” column. In each test case, four of the five groups were used for training, and the remaining group was used for testing. Therefore, each training set included twelve products, and the trained neural network (or students) were tested using the remaining three product function structures. This was done using both ANNs and fourth-year mechanical engineering undergraduate students.

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Table 1. Product information

Products	G #	Functions, Flows	Average MV ($)	Products	G #	Functions, Flows	Average MV ($)
Hair Dryer	1	18, 22	22.28	Mixer	4	20, 29	13.41
Lawn Mower	1	30, 51	126.59	Juice Extractor	4	24, 30	31.98
Solar Yard Light	1	6, 9	2.89	Electric Toothbrush	4	16, 23	104.37
Bench Vise	2	13, 22	40.47	Garage Door Opener	5	34, 50	127.77
Electric Drill	2	35, 59	54.02	Jig Saw	5	17, 39	105.29
Flashlight	2	9, 21	20.32	Sander	5	27, 44	214.95
Nail Gun	3	17, 25	79.72				
Sewing Machine	3	44, 63	114.8				
Stapler	3	31, 39	18.04				

In addition to comparing the predictive capability of ANNs to that of student participants, the value of information within the function structure model representation was also investigated. This was done by separating the two main types of information within the function structure model: the topological information content, and the verbal information content (or the vocabulary) (Sen *et al.*, 2010). Therefore, two versions of each function structure model were created; a function structure model with no function or flow labels (Topo-only) and a version with functions and flows labelled (Topo-Vocab). The Topo-only version is a representation with only topological information, whereas Topo-Vocab is a complete model with both topological information and vocabulary. The experiment was structured to test the predictive capability of participants using either just the topological information or the complete function model. Prediction using only the vocabulary was not tested as part of this experiment. In summary, two independent variables were tested in this experiment: the prediction method (ANN vs students) and the information type (Topo-only vs Topo-Vocab).

2.1. Machine Prediction using ANNs

The general process for converting a function structure model to a bi-partite graph is outlined in Figure 2. Product function structure models are converted into bipartite graphs, which are subsequently used to generate graph complexity metrics (Mathieson *et al.*, 2011; Patel *et al.*, 2016).

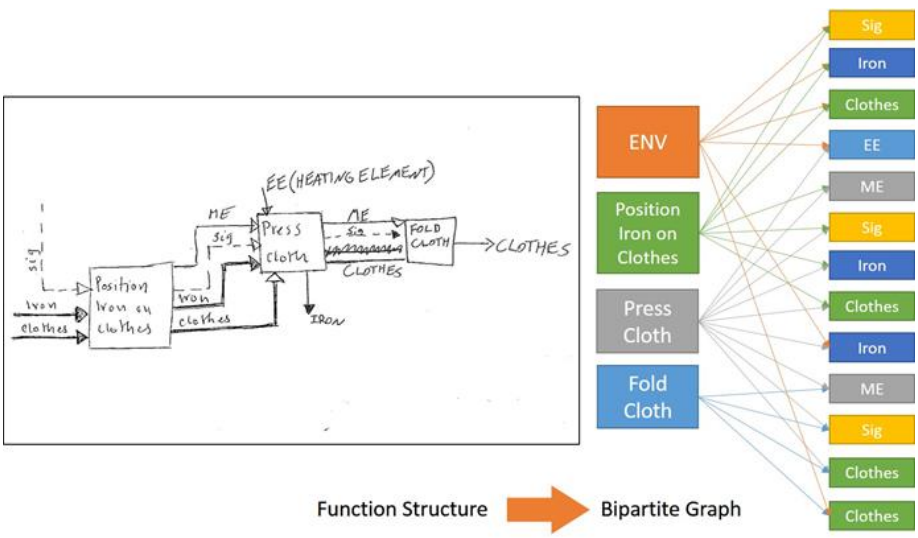

Figure 2. Converting function structure models into bipartite graphs

The topological information content in a function structure model includes the number, arrangement, and interconnections of its constitutive elements (functions and flows). A graph complexity approach

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was used for feeding the topological information into the neural networks. The bipartite graphs are then processed in MATLAB to generate a complexity vector containing 29 complexity metrics. These are composed of four classes of metrics: size, interconnection, centrality, and decomposition (Mathieson et al., 2013; Namouz and Summers, 2013; Patel et al., 2017; Sri Ram Mohinder et al., 2017; Sridhar et al., 2016a). This complexity vector is used as a representation of the topological information in the function structure model and fed into the neural network.

In addition to the topological content, the vocabulary present in the function structure models also needs to be represented in a format suitable for input to the prediction tool. In this case, the Functional Basis was used to transform the vocabulary present in the function structure models into a frequency vector (Table 2), which was then fed to the neural network for prediction. Note that the data presented in Table 2 is separated by functions and flows and represents only part of the frequency vector.

Table 2. Frequency vector for vocabulary

Class	Basic	Lawn Mower	Electric Drill	Class	Basic	Lawn Mower	Electric Drill
Functions				Flows			
Branch	Separate	0	1	Material	HumanM	5	6
	Remove	1	0		Gas	3	0
	Refine	0	0		Liquid	4	0
	Distribute	0	1		Solid	6	8
Channel	Import	8	9		Mixture	3	0
	Export	8	9	Signal	Status	8	0
	Transfer	4	1		Control	8	8
	Transport	0	0	Energy	Mech.	3	20
	Transmit	0	2		Electrical	0	7
	…	…	…	…	…	…	…

The Functional Basis provides a finite set of verbs and nouns to describe the functional transformation and flows respectively. Four levels of specificity are described in the Functional Basis: class, basic, sub-basic, and complements (Hirtz *et al.*, 2002; Stone and Wood, 2000). For the purpose of this research, the second level of specificity, basic, was used to characterize the vocabulary in the function models. In cases where the vocabulary within the product function structures did not match any of the Functional Basis vocabulary, appropriate modifications were made in order to comply with the Functional Basis. A frequency vector was then created which represented the number of times each term was found in the function structure model. This was done for both functions and flows. Portions of the frequency vector for two of the products are shown in Table 2. A total of 32 functions and 19 flows are identified in the basic level of the Functional Basis; a combined vector with 51 elements was used as a representation of the vocabulary in the function structure models. When predicting using topology and vocabulary, the complexity vector of 29 elements was extended to include the 51 elements of the vocabulary frequency vector, resulting in a vector with 80 elements.

2.2. Student Estimation

In addition to ANN, student participants were queried to estimate the market value of products represented by function structure models. Similar to the ANN-based prediction method, student participants were provided one of the two versions of the function structure model: a model without vocabulary information (Topo-only), or a model including vocabulary information (Topo-Vocab). A total of 140 senior-level mechanical engineering students participated in this experiment and were randomly assigned a model version; 73 participants were given Topo-only version of the function structure model and 67 participants were given Topo-Vocab version of the function structure model. Each of these two groups was further divided into five smaller groups; each receiving one set of function structure models based on the k-fold cross validation sets. A breakdown of test assignments is

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shown in Table 3. As previously mentioned, the group number refers to the set of training and test function structure models.

Table 3. Test group assignments

Groups		Group 1	Group 2	Group 3	Group 4	Group 5
Number of Students	Topo-only	13	15	16	16	12
	Topo-Vocab	14	13	14	13	13

An online, survey-based experiment was designed with two independent variables of interest: representation of the function structures (Topo-only or Topo-Vocab) and composition of the training group (five different compositions). The student participants were asked to review the function structure models and associated market values provided in the training group, then estimate market values for new function structure models. While the neural networks were given a numerical vector as an in-put for training, the student participants were given an image of the function structure model, either with vocabulary information as text (Figure 3, right) or without text (Figure 3, left).

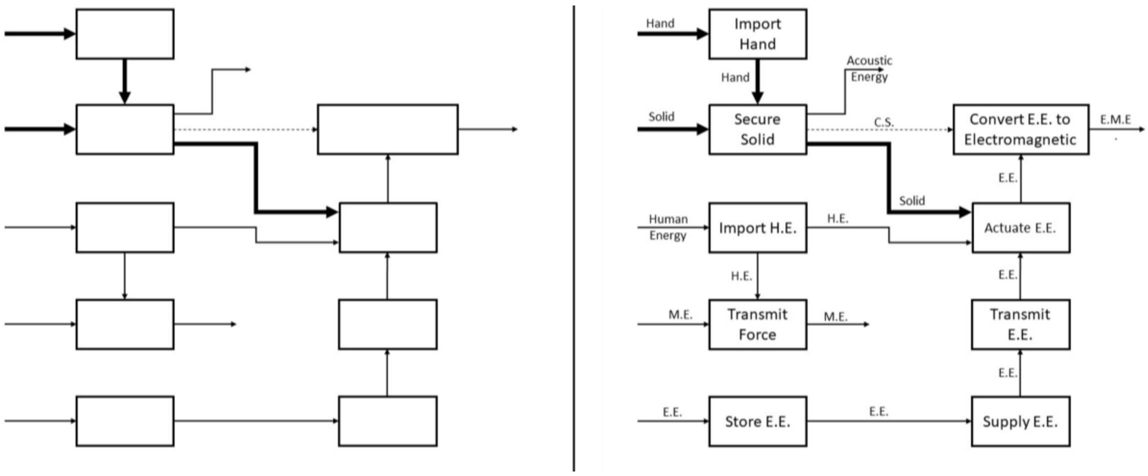

Figure 3. Function model without labels (left) and with labels (right)

Each student participant was provided twelve function structure models with associated market values. Participants were not given any time limit for this activity, and they were allowed to refer to the function structure models and costs at any point during the activity. This was done to allow them sufficient time for reviewing the given materials and forming a process for estimating the market values. The survey was created using Google Forms, and the students were permitted to complete the activity in a location of their choice. An extra credit participation grade was offered to all participants upon successful completion of the activity. As previously mentioned, the function structure models for this experiment were adapted from those available on the design repository. It should be noted that no topological or vocabulary information was changed in the process, they were merely recreated to better serve the purpose of this experiment. As a result, some of the models may appear to be visually different, however, the number of functions and flows, their connectivity, and associated labels were not changed.

3. Results

Student estimates of market values collected from the survey were compared to results from the ANN-based prediction tool. Accuracy and precision of the predictions were compared.

3.1. Prediction Accuracy

As previously mentioned, the ANN-based prediction tool generated 18,900 predictions; an average of these predictions was used as the final prediction. Similarly, multiple student participants predicted the

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market value of each product (see Table 3); an average was used as the final prediction. The average market value predictions for each product are shown in Table 4.

Table 4. Average market value predictions

Product Name	Target	Topology Only		Topo + Vocab	
		ANN	Man	ANN	Man
1. Bench Vise	40.47	85.33	66.50	64.20	57.31
2. Electric Drill	54.02	141.44	113.29	135.31	230.35
3. Elec. Toothbrush	104.37	66.05	44.55	65.54	141.75
4. Flashlight	20.32	137.96	37.83	88.82	72.00
5. Garage Opener	127.77	119.38	86.10	120.22	92.21
6. Hair Dryer	22.28	65.80	46.30	88.96	56.07
7. Jig Saw	105.29	124.95	54.71	124.98	47.67
8. Juice Extractor	31.98	54.22	62.20	53.99	81.33
9. Lawn Mower	126.59	122.97	88.81	91.26	153.89
10. Mixer	13.41	89.50	76.58	88.36	90.12
11. Nail Gun	79.72	27.16	70.89	69.19	72.20
12. Sander	214.95	97.50	81.48	97.62	61.07
13. Sewing Machine	114.80	163.80	147.50	110.37	168.52
14. Solar Yard Light	2.89	52.49	22.85	40.95	1205.75
15. Stapler	18.04	61.54	162.19	121.84	70.82

Predictions closer to the target value, between student estimates and ANN-based predictions, are highlighted. For predictions based on topology only, student predictions were more accurate for eight out of fifteen products compared to machine predictions, which were more accurate for seven out of fifteen products. Alternatively, when using both topology and vocabulary, machine predictions were more accurate eight times, and student predictions were more accurate seven times. Moreover, machine predictions were more accurate in both cases for four products (garage door opener, jig saw, juice extractor, and sander), whereas student predictions were more accurate for four other products (bench vise, flashlight, hair dryer, and nail gun) in both cases. Overall, the results suggest that there is not a significant difference in the accuracy of prediction between students estimates and ANN predictions.

In addition to comparing predictions from ANNs to student estimates, the effects of the type of information provided were also analysed. Figure 4 shows a summary of the prediction error for both machine prediction and student prediction. It should be noted results shown in Figure 4 do not include the data for product 14 (solar yard light), since it was determined to be an outlier in the case of machine predictions as well as student estimates.

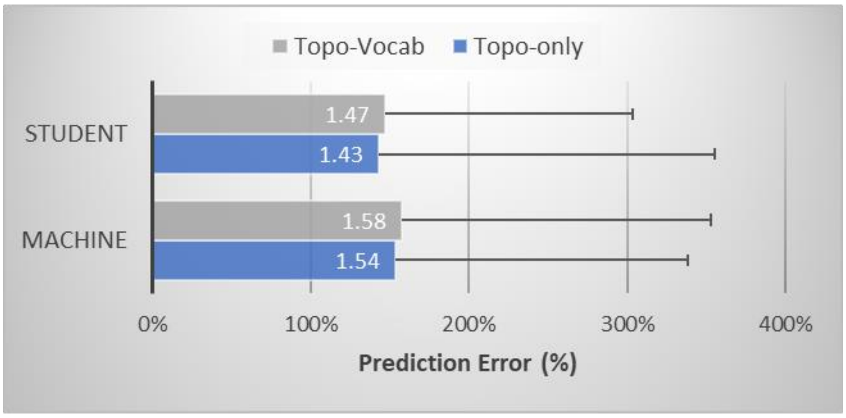

Figure 4. Effects of information type on predictions

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In each case, the addition of vocabulary produced a small increase in the prediction error. For machine prediction, the variance of error was larger when using vocabulary, whereas for student prediction, a smaller variance was observed when using vocabulary. This suggests that the type of information used did not have a significant effect on the prediction error for machine predictions. In the case of students, the introduction of vocabulary resulted in smaller differences in prediction error between products. Overall, from the perspective of accuracy, no significant differences were found between machine predictions and student estimates, or between Topo-only and Topo-Vocab. However, it should be noted that this comparison is for a specific product type and included only fifteen products. Future research should include products from a variety of markets and include a larger number of products to support more robust statistical analysis. Additionally, further analysis may include a comparison of function structure attributes (i.e., elements of the complexity vector and the vocabulary vector) with prediction accuracy. This may reveal similarities and differences between student prediction and ANN predictions based on the size and complexity of the function structure models. This may be useful in categorizing which type of function structure models can be reliably used for prediction using ANNs, and which are better estimated by human beings. Following the analysis of prediction accuracy, the precision in prediction was analysed to determine the spread away from the mean predictions.

3.2. Prediction precision

While the accuracy of the prediction is critical to the usability of a prediction system, the precision of the predictions also plays a role in the level of confidence associated with those predictions. As such, the precision of predictions was analysed by comparing the variance of machine predictions with student participants. Product-by-product results are omitted for brevity. Contrary to the accuracy analysis, the student predictions were found to have smaller variances for all products when using topology only for prediction, and for thirteen out of fifteen products when using topology and vocabulary for prediction. This is an expected result because the machine predictions are an average of 18,900 individual predictions, some of which are generated from a single hidden layer with a single neuron. Comparatively, only twelve to sixteen predictions were obtained for each product in the case of student estimates. Additionally, students are unlikely to estimate a negative value as their prediction for a given product, further improving the expected variance in prediction. Analysing the effect of information type on the prediction precision reveals that the addition of vocabulary information has a non-positive effect on the variance.

For machine prediction, eleven out of fifteen products saw an increase in the variance, with an average increase of 89k. In the case of student estimates, an average increase of 19k was observed, with all products exhibiting a wider spread about the mean prediction. It should be noted that in the analysis of prediction precision, solar yard light was an outlier and removed from the analysis. In summary, student estimates were more precise compared to machine predictions, for Topo-only as well as Topo-Vocab. Alternatively, Topo-only predictions were generally more precise for both students and machine predictions compared to Topo-Vocab.

4. Conclusions

This work presents an experiment conducted to compare the prediction capabilities of artificial neural networks to that of senior-level mechanical engineering students. The predictions were compared based on accuracy and precision. Results show negligible differences between machine predictions and student estimates. This suggests that the ANN-based prediction method was able to perform comparably to students in terms of prediction accuracy. However, when comparing the precision of predictions, student predictions were found to be more precise, resulting in a tighter spread around the mean. Overall, this indicates any single student estimate is more reliable compared to a single prediction from ANNs.

In addition to comparing student estimates to machine predictions, the effects of the type of information used for prediction was also analysed. In both cases, machine prediction and student estimates, the addition of vocabulary resulted in a 4% increase in prediction error, however this was not found to be statistically significant. Alternatively, the addition of vocabulary reduced the difference in prediction error between products in the case of student estimates. Moreover, the addition of vocabulary resulted in a lower precision of predictions, meaning the predictions were less reliable when using vocabulary, for both student and machine predictions.

5. Limitations and future work

This experiment was conducted using only fifteen products, resulting in a data set that is much smaller than what is desired for artificial neural networks. Moreover, the neural networks were comprised of no more than three hidden layers, and no more than 15 neurons in those layers. A deeper network with more training data may provide better predictions compared to what has been presented in this paper. Similarly, the students participating in this experiment were introduced to function structure models the same week of the experiment and may not be adequately familiar with the representation to identify key elements of the models, limiting their ability to draw patterns between the given models and costs. Participants with more experience within the domain of function modelling, and with more knowledge of product functions may provide better estimates.

In addition to addressing these limitations, future work may also investigate the relationship between student confidence in market value prediction and the accuracy and precision of those predictions. The following future research questions can be formulated.

- **RQ**: How does prediction accuracy relate to student confidence in prediction?
- **RQ**: How does prediction precision relate to student confidence in prediction?

The size of function structure models (number of functions and flows) may also be another variable of interest, resulting in the following research questions.

- **RQ**: How does the number of functions in a function structure model affect prediction accuracy and precision?
- **RQ**: How does the number of flows in a function structure model affect prediction accuracy and precision?

These questions should be investigated for both machine prediction and student estimates. Ultimately, future research may be directed towards identifying areas where machine prediction is the better option, and areas where estimates by humans may be sufficient or preferred. Moreover, future work can investigate the prediction accuracy and prediction confidence of experts and novices and compare them with the ANN results. For instance, the effects of training on the final cost estimations can be further investigated.

References

Bengio, Y. and Grandvalet, Y. (2004), "No unbiased estimator of the variance of K-fold cross-validation", Journal of Machine Learning Research, Vol. 5, pp. 1089–1105.

Dieter, G.E. and Schmidt, L.C. (2013), Engineering Design, 5th ed., McGraw-Hill, New York.

Dym, C.L. and Little, P. (2000), Engineering Design: A Project-Based Introduction, John Wiley & Sons, Inc., New York.

Fernández, M.G., Seepersad, C.C., Rosen, D.W., Allen, J.K. and Mistree, F. (2001), "Utility-based decision support for selection in engineering design", Proceedings of the ASME Design Engineering Technical Conference, Vol. 2, pp. 887–899.

Geirhos, R., Janssen, D.H.J., Schütt, H.H., Rauber, J., Bethge, M. and Wichmann, F.A. (2017), "Comparing deep neural networks against humans: object recognition when the signal gets weaker", available at: http://arxiv.org/abs/1706.06969.

Gill, A.S., Summers, J.D. and Turner, C.J. (2017), "Comparing function structures and pruned function structures for market price prediction: An approach to benchmarking representation inferencing value", Artificial Intelligence for Engineering Design, Analysis and Manufacturing, Vol. 31 No. 4, pp. 550–566.

Hirtz, J., Stone, R.B., McAdams, D. a., Szykman, S. and Wood, K.L. (2002), "A functional basis for engineering design: reconciling and evolving previous efforts", Research in Engineering Design, Vol. 13 No. 2, pp. 65–82.

Hoyle, C., Chen, W., Wang, N. and Gomez-Levi, G. (2011), "Understanding and modelling heterogeneity of human preferences for engineering design", Journal of Engineering Design, Vol. 22 No. 8, pp. 583–601.

Lecun, Y., Bengio, Y. and Hinton, G. (2015), "Deep learning", Nature, Vol. 521 No. 7553, pp. 436–444.

https://doi.org/10.1017/pds.2022.169 Published online by Cambridge University Press

Lee, B., Fillingim, K.B., Binder, W.R., Fu, K. and Paredis, C.J.J. (2017), “Design Heuristics: A Conceptual Framework and Preliminary Method for Extraction”, Volume 7: 29th International Conference on Design Theory and Methodology, American Society of Mechanical Engineers, pp. 1–10.

Mathieson, J.L., Shanthakumar, A., Sen, C., Arlitt, R., Summers, J.D. and Stone, R. (2011), “Complexity as a surrogate mapping between function models and market value”, Proceedings of the ASME Design Engineering Technical Conference, Vol. 9, pp. 55–64.

Mathieson, J.L., Wallace, B.A. and Summers, J.D. (2013), “Assembly time modelling through connective complexity metrics”, International Journal of Computer Integrated Manufacturing, Taylor & Francis, Vol. 26 No. 10, pp. 955–967.

McComb, C., Cagan, J. and Kotovsky, K. (2017), “Capturing Human Sequence-Learning Abilities in Configuration Design Tasks Through Markov Chains”, Journal of Mechanical Design, Transactions of the ASME, Vol. 139 No. 9, pp. 1–12.

Namouz, E.Z. and Summers, J.D. (2013), “Complexity Connectivity Metrics-Predicting Assembly Times with Abstract Assembly Models”, in Abramovici, M. and Stark, R. (Eds.), Smart Product Engineering, Springer Berlin Heidelberg, Bochum, Germany, pp. 77–786.

Pahl, G., Beitz, W., Blessing, L., Feldhusen, J., Grote, K.-H.H. and Wallace, K. (2013), Engineering Design: A Systematic Approach, edited by Second, 3rd ed., Vol. 11, Springer-Verlag London Limited, London.

Patel, A., Andrews, P., Summers, J.D., Harrison, E., Schulte, J. and Laine Mears, M. (2017), “Evaluating the Use of Artificial Neural Networks and Graph Complexity to Predict Automotive Assembly Quality Defects”, Journal of Computing and Information Science in Engineering, Vol. 17 No. 3, available at:https://doi.org/10.1115/1.4037179.

Patel, A.R., Gill, A.S., Kramer, W.S., Summers, J.D. and Shuffler-Porter, M.L. (2016), “Graph Complexity Analysis of Function Models Expanded from Partially Completed Models”, in Linsey, J., Yang, M. and Nagai, Y. (Eds.), 4th International Conference on Design Creativity, Atlanta, GA.

Petiot, J.F. and Grognet, S. (2006), “Product design: A vectors field-based approach for preference modelling”, Journal of Engineering Design, Vol. 17 No. 3, pp. 217–233.

Pietila, G. and Lim, T.C. (2015), “Sound quality preference modeling using a nested artificial neural network architecture”, Noise Control Engineering Journal, Vol. 63 No. 2, pp. 138–151.

Raina, A., McComb, C. and Cagan, J. (2019), “Learning to design from humans: Imitating human designers through deep learning”, Proceedings of the ASME Design Engineering Technical Conference, Vol. 2A-2019, pp. 1–13.

Sen, C., Caldwell, B.W., Summers, J.D. and Mocko, G.M. (2010), “Evaluation of the functional basis using an information theoretic approach”, Artificial Intelligence for Engineering Design, Analysis and Manufacturing), Vol. 24 No. 1, p. 87.

Sri Ram Mohinder, C. V., Gill, A. and Summers, J.D. (2017), “Using Graph Complexity Connectivity Method to Predict Information from Design Representations: A Comparative Study”, in Gero, J.S. (Ed.), Design Computing and Cognition ’16, Springer International Publishing, pp. 667–683.

Sridhar, S., Fazelpour, M., Gill, A. and Summers, J.D. (2016a), “Precision Analysis of the Graph Complexity Connectivity Method: Assembly and Function Model”, CIRP CATS 2016, CIRP, Gothenburg, Sweden, p. 01095.

Sridhar, S., Fazelpour, M., Gill, A. and Summers, J.D. (2016b), “Accuracy and Precision Analysis of the Graph Complexity Connectivity Method”, CIRP CATS 2016, CIRP, Gothenburg, Sweden, pp. 163–168.

Stone, R.B. and Wood, K.L. (2000), “Development of a Functional Basis For Design”, Journal of Mechanical Design, Vol. 122 No. December.

Suryadi, D. and Kim, H.M. (2019), “A Data-Driven Methodology to Construct Customer Choice Sets Using Online Data and Customer Reviews”, Journal of Mechanical Design, Vol. 141 No. 11, pp. 1–12.

Ullman, D.G. (1992), The Mechanical Design Process, edited by Corrigan, J.J. and Morriss, J.M., 3rd ed., McGraw-Hill, New York, USA, available at: http://www.cambridge-design.co.uk/.

Visotsky, D., Patel, A. and Summers, J. (2017), “Using Design Requirements for Environmental Assessment of Products: A Historical Based Method”, Procedia CIRP, Elsevier B.V., Vol. 61, pp. 69–74.

Wan, J. and Krishnamurty, S. (2001), “Learning-based preference modeling in engineering design decision–making”, Journal of Mechanical Design, Transactions of the ASME, Vol. 123 No. 2, pp. 191–198.

Wang, J. (2001), “Ranking engineering design concepts using a fuzzy outranking preference model”, Fuzzy Sets and Systems, Vol. 119 No. 1, pp. 161–170.

Yang, J.B. and Sen, P. (1996), “Preference modelling by estimating local utility functions for multiobjective optimization”, European Journal of Operational Research, Vol. 95 No. 1, pp. 115–138.