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Accuracy and Precision Analysis of the Graph Complexity Connectivity Method

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Abstract

For a given electro-mechanical product, represented using assembly models and function structures, the assembly time (AT) and market value (MV) are influenced by complexity of the product. Given the AT and MV of a set of known products, complexity values can be used to predicted AT and MV for a set of unknown products using an Artificial Neural Network. This paper presents a precision analysis of four prediction models that are a combination of the aforementioned design representations and AT and MV. A sensitivity analysis of the complexity metrics was done using Multiple Linear Regression, and a set of significant metrics was identified. Lastly, a comparison of accuracy and precision for the four prediction models obtained using this set of sensitivity analysis is presented.

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Keywords: Assembly models; Function structures; Assembly time; Market value; Artificial neural network

1. Complexity in engineering design

One of the measures for evaluating and comparing solutions in engineering design is simplicity [1–3]. Complexity can be considered as a measure of simplicity when comparing solutions. Evaluating a design problem as regards to complexity yields an important measure during the development of design support systems as problems and processes are objectively and computably compared with suitable applications [4]. Complexity is a term which is usually used to elucidate an attribute, which is hard to quantify precisely [5]. Research has been conducted on measuring system complexities within specific domains, such as engineering design, information theory, and computer science [6]. An initial challenge is to develop an objective and representation independent method that can help measure system complexities across domains. Considering the large number of system variables that contribute to complexity, it is difficult to evaluate it through a single metric. For instance, size (system element count) and coupling (connectivity between elements) are both views of complexity that are related but not interdependent [7]. Therefore, previous research has focused on measuring complexity in engineering design based on multiple metrics [7–10].

The existing complexity measurement methods refer to the term complexity with different interpretations [1,4,10]. In the context of this research, the following definitions would best describe the term complexity:

- The amount of information required to describe a system comprised of more than one component [4,11].
- The interconnections between elements which allow a given system to take on properties and behaviors which the collection of elements would not exhibit on its own [12].

Various approaches have been taken across disciplines in order to quantify complexity in design with respect to evaluating systems, algorithms, information, or design [4]. This paper uses graph complexity connectivity method that present in detains in the next section.

1.1. Graph complexity connectivity method (GCCM)

Complexity metrics measured using graph topologies can be used to create early stage surrogate prediction models of assembly time, when product assembly models are given [9,10,12] and market cost, or when function structures are

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given [8,13]. Bi-partite graphs are used as a representation of the system’s architecture, and track the connections between the system’s constituent elements [15].

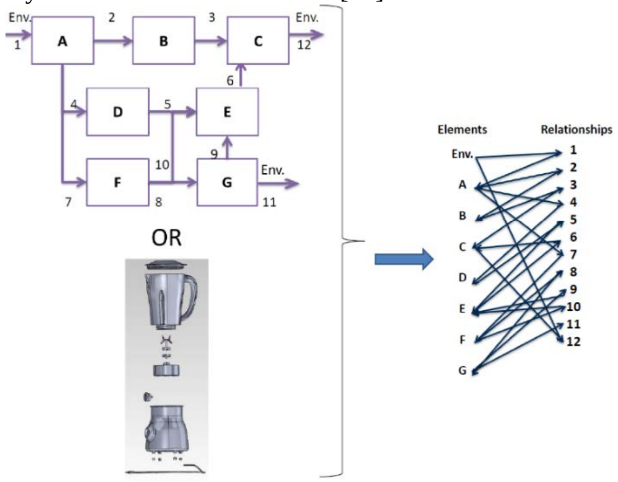

Fig. 1. Representation of a blender architecture as a bi-partite graph [14].

In this approach the graphs are evaluated against the structural complexity metrics to form a complexity vector describing each product. Unlike previous approaches that treat complexity as a single value [15,16], this one takes the unique approach of treating complexity as a combination of different influential properties: size, interconnectivity, centrality, and decomposition. The complete set of twenty nine complexity metrics is listed in Table 1.

Table 1. Twenty nine complexity metrics [13].

Class	Type	Direction	Metrics
			Comp. vector
Size	Dimensional		Elements
			Relationships
	Connective		DOF
			Connections
Interconnection	Shortest Path		Sum
			Max
			Mean
			Density
	Flow Rate		Sum
			Max
			Mean
			Density
Centrality	Betweenness		Sum
			Max
			Mean
			Density
	Clustering Coefficient		Sum
			Max
			Mean
			Density
Decomposition	Ameri Summers		
	Core Numbers	In	Sum
			Max
			Mean
			Density
		Out	Sum
			Max
			Mean
			Density

To assess its potential utility value, the GCCM was compared to the Boothroyd and Dewhurst method based on predicted assembly time, analysis duration, input information and its nature: objectivity v/s subjectivity [17]. The predicted assembly times of the GCCM approximately ranged from 13% to 49%, lower than the predicted times of the DFMA software which was considered to be the benchmark. Due to the extensive effort required to create the bi-partite graphs using the GCCM, the Assembly Mate Method (AMM) was incorporated which uses SolidWorks (SW) assembly mate information to create the connectivity graphs needed for the GCCM [18]. Continuing the previous work, two separate neural networks were created and compared: the first ANN which uses the complexity vector of the high-fidelity models as input and assembly times as the targets, and the second ANN which uses the complexity vectors of the low-fidelity models as the training inputs and the same assembly times as target times [19]. Results indicated that the assembly time of a product can be predicted to within 40% of the target as built time using a high fidelity neural network and a low fidelity CAD model [19].

As mentioned earlier, the GCCM has demonstrated that structural complexity metrics applied against graph topologies can be used to create prediction models of assembly time given product assembly models [9,10,12] and market cost given function structures [13]. Recent advances in the method show that each of the two representations, Function Structures and Assembly Models can be used to predict both the performance values, Market Price and Assembly Time [8].

1.2. Motivation on evaluating precision of surrogate prediction models to estimate assembly time and market value

The research efforts in this method have been focused on the development of surrogate prediction models [8,18]. These prediction models use engineering design representations of assembly models and function structures to predict product performance values of assembly time and market value. The performance of these prediction models has been previously assessed solely based on accuracy. In this research, the predictive precision of the surrogate models is evaluated in order to assess the GCCM's ability to generate consistent results under the same conditions. The accuracy and precision of the estimated performance values will be used to assess the performance of the prediction models. Here, accuracy is defined as the “correctness” of a prediction or the distance from the target value. Precision is defined as the size of the variation of the results from the model. A prediction model which is both accurate and precise can generate consistent results each time (repeatability) under the same conditions. This assessment will enable engineers to consider the impacts of their decisions on product performance in the early stages of design using exact quantifiers rather than anecdotal experience. It would facilitate methodical comparison and application of the appropriate engineering design representations for estimating performance values in a design project.

The second contribution of this work lies into understanding complexity as an enabler in prediction. This will be accomplished by identifying the complexity metrics that are influential in predicting the product performance values for each of the four surrogate prediction models.

2. Prediction method

To examine the precision of the design representations (assembly models and function structures) in predicting the performance values of the products (assembly time and market value), four surrogate prediction models are listed in Table 2.

Table 2. Design representation based surrogate prediction models.

S No.	Graph Models	Performance Value
1	Assembly Models	Assembly Time
2	Assembly Models	Market Value
3	Function Structures	Assembly Time
4	Function Structures	Market Value

The experimental method utilizes a data set of twenty electro-mechanical consumer products for performance value prediction. The samples of products include stapler, electric grill, electric drill, and jigsaw. The complete list of products listed in [14]. Fifteen out of these twenty products are applied for training the ANNs and the remaining five tested using the trained ANNs. The products are characterized into two design representations: function structures and assembly models. This provides a diversity in product design representation in that the assembly models represent a product's form dependent blueprint whereas the function structures constitute a product's form independent blueprint [20]. Thus the method is not dependent on an engineer's interpretation of product design, but rather on the design representation. This helps in developing objective measures of complexity.

2.1. Evaluation of predictive precision

The predictive error (PE) is given by the difference between the estimated and the target performance value and is calculated using Eq. 1 [14].

$$\%\,\mathrm{PE} = \frac{\mathrm{PE}}{\left|\mathrm{Performance\_Target}\right|} \times 100 \qquad (1)$$

To quantify the amount of variation in data distribution, the standard deviation of the percentage predictive error (Predictive Precision) for the five test products is then evaluated using Eq. 2 [14].

$$\mathrm{Predictive\_Precision} = \sqrt{\frac{\sum\left(\%\,\mathrm{PE} - \overline{\%\,\mathrm{PE}}\right)^2}{\mathrm{Num\_Estimates}}} \qquad (2)$$

2.2. Comparison of precision and accuracy of prediction models

The precision analysis is conducted for five test products across the four prediction models. The standard deviation of the absolute percentage error is used as the measure to indicate predictive precision. The prediction model with the lowest standard deviation value indicates highest precision in predicting the performance values and vice versa. The four prediction models are each assigned a rank from 1 through 4 depending on the absolute percentage error standard deviation (predictive precision) of the performance estimates with 1 as most precise and 4 as least precise. The predictive precision ranking of the four models for each of the five products is illustrated in Table 3 (FS-AT: Function structure - Assembly Time, AM-AT: Assembly model - Assembly Time, FS-MV: Function Structure - Market Value, FS-AT: Function Structure - Assembly Time).

Table 3. Predictive Precision ranking of the prediction models.

Products	FS-AT	AM-AT	FS-MV	AM-AV
Sander	1.0	3.0	1.0	3.0
Hairdryer	2.0	1.0	3.0	4.0
Lawnmower	4.0	1.0	3.0	2.0
Flashlight	2.0	1.0	3.0	4.0
Food Chopper	1.0	1.0	3.0	4.0
Best Rank	1.0	1.0	1.0	2.0
Worst Rank	4.0	3.0	3.0	4.0
Mean Rank	2.0	1.4	2.6	3.4
Mode Rank	2.0	1.0	3.0	4.0

3. Identification of sensitivity metrics

This section will deal with the identification of significant complexity metrics for each of the four surrogate models discussed in the previous section. Multiple linear regression is the statistical technique used to conduct the sensitivity analysis of the twenty nine complexity metrics in performance value prediction for the four prediction models. The sensitivity analysis of the metrics as predictors through the ANNs can also be used to avoid the limitation of the low data set size associated with the high degree of freedom of the 29 complexity metrics.

3.1 Procedure for determining significant metrics

The twenty nine complexity metrics are used as the explanatory variables and the 18,900 performance value estimates are used as the response variables for the stepwise multiple linear regression analysis of the 15 training products. The standard stepwise selection procedure is a combination of the forward selection and backward elimination procedures. After each step in which a variable is added, all the applicant variables in the model are inspected to see if their significance has been reduced below the specified tolerance level. Hence, the standard stepwise variable selection procedure is selected for this analysis. Due to a small sample size comprising of five test products and fifteen training products, a wide confidence interval of 90% is used. The 'Alpha-to-remove' value of 0.1 is used as the indicator for a variable's significance. A two-sided confidence interval of 90% is used for the analysis.

3.1 Results for the sensitivity analysis

The significant predictors for Assembly Model- Assembly Time and Assembly Model-Market Value have been tabulated in Table 4.

The significant predictors from Function Structure-Assembly Time and Function Structure- Market Value have been tabulated in Table 5. The significant predictor metrics identified across each of the four prediction models are m1 and m25.

Table 4. Significant predictors of the AM-AT and AM-MV prediction models.

AM - AT					AM - MV				
Class	**Type: Metric**	**Metric #**	**Coefficient**	**p-value**	**Class**	**Type: Metric**	**Metric #**	**Coefficient**	**p-value**
Size	Dimensional : Elements	m1	0.487	0.036	Size	Dimensional: Elements	m1	0.476	0.051
Interconnection	Shortest path: Sum	m5	0.026	0	Interconnection	Shortest path: Sum	m5	0.026	0
Interconnection	Shortest path: Density	m8	-361.5	0	Interconnection	Shortest path: Density	m8	-365.6	0
Interconnection	Flow rate: Mean	m11	-12.522	0	Interconnection	Flow rate: Mean	m11	-12.558	0
Centrality	Clustering Coefficient: Sum	m17	2.486	0	Centrality	Clustering Coefficient: Sum	m17	2.49	0
Centrality	Clustering Coefficient: Max	m18	-14.29	0	Centrality	Clustering Coefficient: Max	m18	14.37	0
Centrality	Clustering Coefficient: Density	m20	-999	0	Centrality	Clustering Coefficient: Density	m20	-999	0
Decomposition	Core numbers In: Sum	m22	0.202	0.073	Decomposition	Core numbers In: Sum	m22	0.198	0.079
Decomposition	Core numbers In: Density	m25	148	0.031	Decomposition	Core numbers In: Density	m25	150.3	0.026

Table 5. Significant predictors of the FS-AT and FS-MV prediction models.

FS - AT					FS - MV				
Class	**Type: Metric**	**Metric #**	**Coefficient**	**p-value**	**Class**	**Type: Metric**	**Metric #**	**Coefficient**	**p-value**
Size	Dimensional: Elements	m1	0.476	0.051	Size	Dimensional: Elements	m1	13.05	0
Interconnection	Shortest path: Sum	m5	0.026	0	Size	Connective: Connections	m4	1.561	0.044
Interconnection	Shortest path: Density	m8	-365.6	0	Interconnection	Flow rate: Sum	m9	-0.296	0
Interconnection	Flow rate: Mean	m11	-12.558	0	Interconnection	Flow rate: Max	m10	-4.74	0.044
Centrality	Clustering Coefficient: Sum	m17	2.49	0	Interconnection	Flow rate: Density	m12	741	0
Centrality	Clustering Coefficient: Max	m18	14.37	0	Centrality	Betweenness : Sum	m13	0.014	0.002
Centrality	Clustering Coefficient: Density	m20	-999	0	Decomposition	Core numbers In: Density	m25	1012	0.014
Decomposition	Core numbers In: Sum	m22	0.198	0.079	Decomposition	Core numbers Out: Density	m29	-1798	0
Decomposition	Core numbers In: Density	m25	150.3	0.026					

3.2 Evaluation of Accuracy and precision using Significant Metrics

Once the significant metrics have been identified, the ANNs were trained and tested using these metrics instead of the complete set of 29 metrics. The test results have been depicted in Table 6. The prediction models and products where the accuracy or precision has decreased have been shaded in grey.

The test results suggest that on the whole the precision of the prediction models increases when the significant metric set is used for prediction instead of the complete set of twenty nine complexity metrics. This is an indicator that employing only the significant sets of complexity metrics for prediction improves the Graph Complexity Connectivity Method's ability to produce consistent results under the same conditions. There is however a decrease in the predictive accuracy of most of the prediction models while using the significant metrics.

These results indicate that further work needs to be conducted in an attempt to shift these precise measurements towards the target value. This can be achieved by training and testing the artificial neural networks using consumer products that have similar product architectures or those from within the same category of consumer products. For instance, exclusive use of products those fall under the category of consumer power tools [10].

In spite of their relatively low prediction accuracy, these significant complexity metrics can still prove to be valuable predictors of later stage information considering the fact that they are evaluated using early design stage representations while the product structural information available is minimal. These significant metrics will enable designers to consider the impacts of their decisions in the early design stage using exact quantifiers rather than subjective judgments.

4. Experimentation with different sets of significant metrics

In the previous section, it was found that the significant complexity metric sets for the FS-AT, AM-AT, and AM-MV prediction models consist of nine metrics each whereas the significant metric set for the FS-MV prediction model consists of eight metrics. In this section, randomized experiments will be conducted on these datasets.

The dataset for experiment 1 consists of the union of the metrics significant across both the FS-AT and FS-MV models. Experiment 2 includes the significant metrics that are common among the FS-AT and FS-MV models. The metrics identified to be significant predictors for the AM-AT and AM-MV prediction models are identical.

The union and intersection sets of these metrics would result in the same set of metrics. This is the reason why experiments 1 and 2 are not conducted for the AM-AT and AM-MV models. The experiment 3 is conducted for a comprehensive set involving the union of all the significant metrics across each of the four prediction models. The result for experiment 1, 2 and 3 have been tabulated in Tables 7, 8, and 9 respectively. The prediction models and products where the accuracy or precision has decreased have been shaded in grey.

For these experiments the values falling within a range of $\pm$15% from each other are considered to be equivalent to each other. Hence, only those changes in accuracy and precision which are beyond the $\pm$15% range are considered to be suggestive.

4.1 Evaluation of Accuracy and precision for the three experiment cases

In the results from experiment 1, the sole considerable change observed for the test product sander, when the experiment 1 metric set is used, is the increase in predictive accuracy. Therefore, it is recommended to use the experiment

1 metric set for predicting the performance values of the sander. For the hair dryer and flashlight, the predictive accuracy and precision are reduced considerably when the experiment 1 metric set is used.

it is recommended to use the significant metrics instead of the test metrics, and vice versa.

For experiment 3 predictive accuracy and precision is reduced considerably for the sander. For the hair dryer and

Table 6. Change in prediction accuracy and precision of five test products for all four prediction models using only the significant metrics

Product ⇨	Sander				Hair Dryer				Lawn Mower				Flashlight				Food Chopper			
Evaluation ⇨	Accuracy		Precision		Accuracy		Precision		Accuracy		Precision		Accuracy		Precision		Accuracy		Precision	
Predictive Model ⇩	Significant Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Significant Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Significant Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Significant Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Significant Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Significant Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Significant Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Significant Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Significant Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Significant Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)
FS-AT	40.4	19.51	88.51	-14.99	24.91	17.21	65.84	167.96	29.35	-14.88	93.59	121.51	9.06	9.92	64.33	165.57	17.68	-8.92	58.74	-1.05
AM-AT	38.26	-28	66.85	83.05	32.5	-25.01	133.8	-20.4	32.16	-31.97	54.85	31.59	140.1	-137.19	186.1	-9.5	32.54	-26.8	53.86	-3.98
FS-MV	72.02	-12.7	20.68	53.94	127.6	5.1	193.2	746.6	43.53	-21.84	44.38	113.32	210.7	-174.66	220.1	155.7	3.22	10.71	91.17	42.73
AM-MV	71.96	-60.1	16.47	135.73	28.11	-15.7	172.4	1355.6	58.26	-51.06	35.21	89.89	0.94	22.29	242.1	1432.9	34.45	-28.33	95.25	207.45

Table 7. Change in prediction accuracy and precision of five test products using only the experiment 1 metrics

Product ⇨	Sander				Hair Dryer				Lawn Mower				Flashlight				Food Chopper			
Evaluation ⇨	Accuracy		Precision		Accuracy		Precision		Accuracy		Precision		Accuracy		Precision		Accuracy		Precision	
Predictive Model ⇩	Experiment 1 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 1 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Experiment 1 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 1 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Experiment 1 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 1 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Experiment 1 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 1 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Experiment 1Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 1 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)
FS-AT	51.14	-10.74	89.61	-1.1	81.85	-56.94	165.3	-99.46	10.28	19.07	68.76	24.83	247	-237.94	202.8	-138.47	39.25	-21.57	45.46	13.28
FS-MV	54.38	17.64	31.23	-10.55	231.6	-104	261.9	-68.7	23.97	19.56	58	-13.62	285.7	-75	293.5	-73.4	13.4	-10.18	105.9	-14.73

Table 8. Change in prediction accuracy and precision of five test products using only the experiment 2 metrics

Product ⇨	Sander				Hair Dryer				Lawn Mower				Flashlight				Food Chopper			
Evaluation ⇨	Accuracy		Precision		Accuracy		Precision		Accuracy		Precision		Accuracy		Precision		Accuracy		Precision	
Predictive Model ⇩	Experiment 2 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 2 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Experiment 2 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 2 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Experiment 2 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 2 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Experiment 2 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 2 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Experiment 2 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 2 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)
FS-AT	37.08	3.32	79.12	9.39	82.01	-57.1	145.8	-79.96	4.93	24.42	65.26	28.33	226.6	-217.54	173.9	-109.57	45.2	-27.52	36.73	22.01
FS-MV	57.81	14.21	25.01	-4.33	231	-103.4	234.5	-41.3	33.59	9.94	46.38	-2	254.9	-44.2	229.7	-9.6	17.5	-14.28	90.77	0.4

Table 9. Change in prediction accuracy and precision of five test products using only the experiment 3 metrics

Product ⇨	Sander				Hair Dryer				Lawn Mower				Flashlight				Food Chopper			
Evaluation ⇨	Accuracy		Precision		Accuracy		Precision		Accuracy		Precision		Accuracy		Precision		Accuracy		Precision	
Predictive Model ⇩	Experiment 3 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 3 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Experiment 3 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 3 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Experiment 3 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 3 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Experiment 3 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 3 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)	Experiment 3 Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Experiment 3 Absolute Percentage Error Standard Deviation (%)	Change in Error Standard Deviation (%)
FS-AT	67.39	-26.99	84.55	3.96	62.17	-37.26	181.1	-115.26	10.3	19.05	61.05	32.54	368.6	-359.54	331.5	-267.17	30.11	-12.43	43.52	15.22
AM-AT	53.46	-15.2	60.71	6.14	58.98	-26.48	114	19.8	-114.4	146.56	93.22	-38.37	190.4	-50.3	187.3	-1.2	59.99	-27.45	55.96	-2.1
FS-MV	96.43	-24.41	51.71	-31.03	59.25	68.35	58.45	134.75	89.54	-46.01	60.25	-15.87	60.95	149.75	89.69	130.41	40.07	-36.85	49.92	41.25
AM-MV	74.6	-2.64	24.17	-7.7	99.34	-71.23	219.1	-46.7	-93.33	151.59	76.62	-41.41	288.9	-287.96	343.2	-101.1	-71.48	105.93	163.3	-68.05

This is the case of both the FS-AT and FS-MV prediction models. The only considerable reduction in accuracy is observed for the food chopper. For the cases where predictive accuracy and precision decreases, it is recommended to use the significant metrics instead of the test metrics, and vice versa.

For experiment 2, the test results for the sander show no considerable changes in either predictive accuracy or precision in the case of both the FS-AT and FS-MV prediction models. For the hair dryer and flashlight's FS-AT and FS-MV models, the predictive accuracy and precision are reduces considerably. For the lawn mower, the experiment 2 metric set improves the predictive accuracy and precision for the FS-AT prediction model not much change is observed for the FS-MV prediction model. The predictive accuracy for the food chopper decreases while the precision increases for the FS-AT prediction model. For the cases where predictive accuracy and precision reduces, it is recommended to use the significant metrics instead of the test metrics, and vice versa.

flashlight, there is both a decrease and increase in the predictive accuracy and precision when the experiment this metric set is used. On the whole, there is a decrease in predictive accuracy and precision in 5 out of 8 cases. For the cases where predictive accuracy and precision reduces, it is recommended to use the significant metrics instead of the test metrics, and vice versa. The test results for the lawn mower and food chopper are inconclusive to make a recommendation on the metric set to be used for prediction, since there are equal number of positive and negative changes in predictive accuracy and precision. Thus, experiment 3, which contains the union of all the significant metrics from the four prediction models, does not improve predictive accuracy and precision when compared to the significant metric sets because each set comprises of complexity metrics that are influential for the specific prediction model.

5. Conclusion and future work

In this study, a precision rank order was determined for each of the four surrogate prediction models on the basis of the absolute percentage error standard deviation of the evaluation of the predictive accuracy [8] and precision rank orders of the four prediction models order to assess the predictive performance of the design representations in estimating the performance values was conducted. It is understood that the assembly models do not contain information regarding all the factors, and this contributes towards lack of precision. A sensitivity analysis of the complexity metrics was also done. The results suggest that for each design representation, there exists a set of complexity metrics that are significant predictors of performance values. There exists at least one metric from each class (size, interconnection, centrality, and decomposition) which is identified as a significant predictor. The centrality metrics are found to be significant for the assembly model design representation as compared to the function structures. This is so because the product dataset analysed comprises of consumer products that are generally designed to be highly modular for ease of manufacturing and assembly. The significant complexity metrics were further used to train and test the ANNs, instead of the original set of twenty nine complexity metrics.

The test results suggested that on the whole the precision of the prediction models increases but the predictive accuracy decreases when the significant metric set is used for prediction. From the experimental done in section 4 it was found that the unique significant metric sets identified specifically for each prediction model work best when used for predicting the performance value estimates of the corresponding model.

The future work will address the issue of variation of predictive accuracy of the significant metric when products belonging to the same category are used for training and testing. Also, other applications of GCCM extended to predict other performance values, such as product defects using assembly models, needs to be explored.

References

[1] Suh, N., 1999, “A Theory of Complexity, Periodicity, and the Design Axioms,” Res. Eng. Des., **11**, pp. 116–131.

[2] Pahl, G., Beitz, W., Feldhusen, J., and Grote, K.-H., 2007, Engineering Design, Springer-Verlag London, London.

[3] Ullman, D., 2009, The Mechanical Design Process, McGraw-Hill Education.

[4] Ameri, F., Summers, J. D., Mocko, G. M., and Porter, M., 2008, “Engineering design complexity: an investigation of methods and measures,” Res. Eng. Des., **19**(2), pp. 161–179.

[5] Caprace, J. D., and Rigo, P., 2012, “A Real-Time Assessment of the Ship Design Complexity,” Comput. Aided Des., **44**(3), pp. 203–208.

[6] Du, D., and Ko, K., 2000, Theory of Computational Complexity, John Wiley and Sons, New York, NY.

[7] Summers, J. D., and Shah, J. J., 2010, “Mechanical Engineering Design Complexity Metrics: Size, Coupling, and Solvability,” J. Mech. Des., **132**(2), p. 021004.

[8] Vasala, S., 2014, “A Comparative Study: Structural Complexity Metrics Applied Against Function and Assembly Product Graphs in Predicting Market Price and Assembly Time,” Clemson University.

[9] Namouz, E., and Summers, J. D., 2014, “Comparison of Graph Generation Methods for Structural Complexity Based Assembly Time Estimation,” ASME Trans. J. Comput. Inf. Sci. Eng., **14**(2), p. 021003.

[10] Owensby, J. E., and Summers, J. D., 2014, “Assembly time estimation: Assembly mate based structural complexity metric predictive modeling,” J. Comput. Inf. Sci. Eng., **14**(1), p. 11004.

[11] Braha, D., and Maimon, O., 1998, “The Measurement of a Design Structural and Functional Complexity,” IEEE Trans. Syst. Man, Cybern. (Part A - Syst. Humans), **28**(4), pp. 527–535.

[12] Mathieson, J. L., Wallace, B. A., and Summers, J. D., 2013, “Assembly time modelling through connective complexity metrics,” Int. J. Comput. Integr. Manuf., **26**(10), pp. 955–67.

[13] 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,” ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, ASME, Washington, DC, pp. DETC2011–47481.

[14] Sridhar, S., 2015, “Sensitivity and Precision Analysis of the Graph Complexity Connectivity Method,” Clemson University.

[15] Bashir, H. A., and Thomson, V., 2001, “An Analogy-Based Model for Estimating Design Effort,” Des. Stud., **22**, pp. 157–167.

[16] Sinha, K., and de Weck, O. L., 2013, “A network-based structural complexity metric for engineered complex systems,” Systems Conference (SysCon), 2013 IEEE International, pp. 426–430.

[17] Owensby, E., Shanthakumar, A., Rayate, V., Namouz, E. Z., and Summers, J. D., 2011, “Evaluation and Comparison of Two Design for Assembly Methods: Subjectivity of Information,” ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, ASME, Washington, DC, pp. DETC2011–47530.

[18] Owensby, J. E., Namouz, E. Z., Shanthakumar, A., and Summers, J. D., 2012, “Representation: Extracting Mate Complexity from Assembly Models to Automatically Predict Assembly Times,” ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, ASME, Chicago, IL, pp. DETC2012–70995.

[19] Namouz, E. Z., and Summers, J. D., 2013, “Complexity Connectivity Metrics – Predicting Assembly Times with Low Fidelity Assembly CAD Models,” Springer, Bochum, Germany.

[20] Stone, R. B., and Wood, K. L., 2000, “Development of a Functional Basis for Design,” J. Mech. Des., **122**(4), pp. 359–370.