

Statistical Analysis to identify the significant design complexity metrics in the estimation of product assembly time and market value

Sudarshan Sridhar, sudarss@clmson.edu

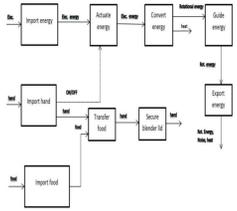
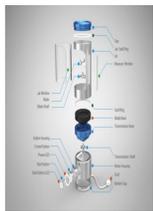
Advisor: Dr. Joshua Summers, jsummer@clmson.edu

Department of Mechanical Engineering, Clemson University, SC

Background

Previous research focused on developing four prediction models:

1. Assembly time estimation based on assembly models
2. Market value estimation based on function structures
3. Market value estimation based on assembly models
4. Assembly time estimation based on function structures



Assembly Model (AM)

Function Structure (FS)



Assembly Time (AT)



Market Value (MV)

Figure: Four Prediction models

Motivation

1. Identify the complexity metrics which are significant predictors of assembly time and market value
2. See whether the set of significant metrics improves the prediction accuracy as compared to the original set of metrics
3. Analyze the metrics which are significant across all the four models
4. Figure out which characteristics make them significant independent of the output being predicted
5. These metrics can be used as the fundamental predictors for other design applications

Experimental Method

- 1) Generate function structures and assembly models of products

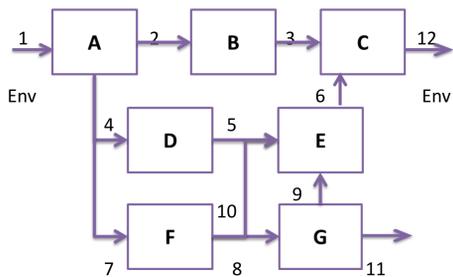


Figure: Function structure

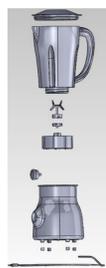


Figure: Assembly model

- 2) Create bi-partite graphs of these structures and models

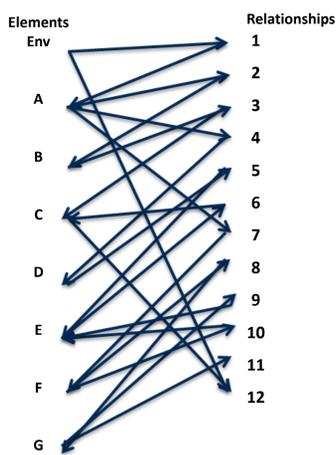


Figure: Bi-partite graph

- 3) Build the 29 complexity metric vector metric using these graphs

Class	Type	Dir.	Metrics	
Size	Dim		Comp. vector	
			1 Elements	
	Conn		2 Rel	
			3 DOF	
Interconnection	Shortest Path		4 Conn	
			5 Sum	
			6 Max	
			7 Mean	
	Flow Rate		8 Density	
			9 Sum	
			10 Max	
			11 mean	
Centrality	Betweenness		12 density	
			13 sum	
			14 max	
			15 mean	
	Clustering Coefficient		16 density	
			17 sum	
			18 max	
			19 mean	
Decomposition	Core Numbers		20 density	
			21 Ameri Summers	
		In		22 sum
				23 max
		Out		24 mean
				25 density
			26 sum	
			27 max	
			28 mean	
			29 density	

Figure: 29 Complexity metrics

- 4) Store Assembly Times and Market Values of Products as Target Values
- 5) Train Artificial Neural Networks(ANNs) using Complexity Metrics and Target Values
- 6) Test the five selected products against the trained Artificial Neural Networks
- 7) Analysis of the test results

Research outline

- ANN is trained using complexity vector of each product as input and the known market value/assembly time as the training target
- ANN design used generates 189 architectures with 100 repetitions each
- This results in 18900 market value/assembly time estimates
- Multiple linear regression is conducted to identify the complexity metrics which are significant predictors
- For the analysis, the 29 complexity metrics are used as the explanatory variables and the 18900 estimates are used as the response variables
- This regression analysis is done for all the four prediction models

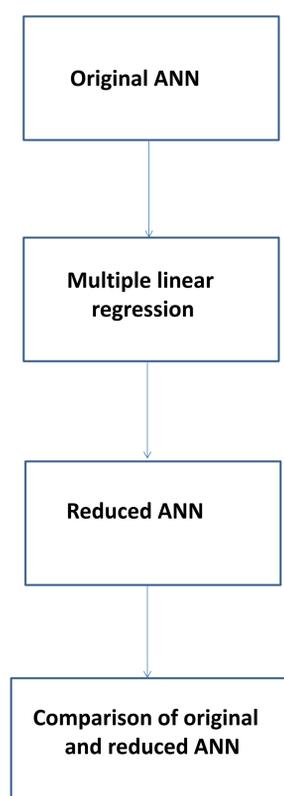


Figure: Research outline

Analysis

Parameters:

Confidence level for all intervals: 90 (i.e. Alpha= 0.1)

Type of confidence interval: Two-sided

Method: Stepwise selection

Software used: Minitab

Results

	AT	MV
FS	Metric no. 1, 4, 9, 10, 11, 12, 14, 25, 29	Metric no. 1, 4, 9, 10, 12, 13, 25, 29
AM	Metric no. 1, 5, 8, 11, 17, 18, 20, 22, 25	Metric no. 1, 5, 8, 11, 17, 18, 20, 22, 25

Figure: Significant metrics for the four combinations

- These significant metrics will now be used to train the ANN
- This ANN is a reduced ANN since not all of the original 29 metrics are used for the training
- The five test products will then be tested against the reduced ANN
- The results obtained would be compared to the results from the original ANN

Conclusions

- Interconnection is a significant predictor across all the four prediction models
- In AM prediction models, centrality and interconnection have the most number of significant metrics
- In FS prediction models, interconnection has the most number of significant metrics
- AMs comprises of parts which are connected to other parts whereas FS is like a tree wherein you have different levels. So not every source/sink will have multiple connections.
- Centrality is significant for AMs as the more central a component is to the others makes the assembly either easier or difficult

Advantages

- Using this information, designers can develop multiple design solutions with more focus on the significant metrics
- Helps channelize design concept development efforts in the right direction
- Reduces computation time and effort

New research questions identified

- Can this experimental method be applied to predict other design parameters such as quality
- Find out which characteristics make certain metrics significant across all the four models
- Would the significant predictors be the same for a different set of training and test products

Acknowledgements

[1] James L. Mathieson, Bradley A. Wallace, Joshua D. Summers, "Assembly time modelling through connectivity complexity metrics", International Journal of Computer Integrated Manufacturing, 2012

[2] Joseph Owensby, "Automated Assembly Time Prediction Tool Using Predefined Mates From CAD Assemblies", 2012

[3] Essam Z. Namouz, Joshua D. Summers, "Complexity Connectivity Metrics - Predicting Assembly Times with Low Fidelity Assembly CAD Models", ASME 2012 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference

[4] James L. Mathieson, Joshua D. Summers, "Complexity metrics for directional node-link system representations: theory and applications", ASME 2010 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference

[5] Farhad Ameri, Joshua D. Summers, Gregory M. Mocko, Matthew Porter, "Engineering design complexity: an investigation of methods and measures",

[6] Kaushik Sinha, "Structural complexity quantification for engineered complex systems and implications on system architecture and design", ASME IDETC/CIE, 2013