ANNs and Complexity Metrics: Predicting Quality Control

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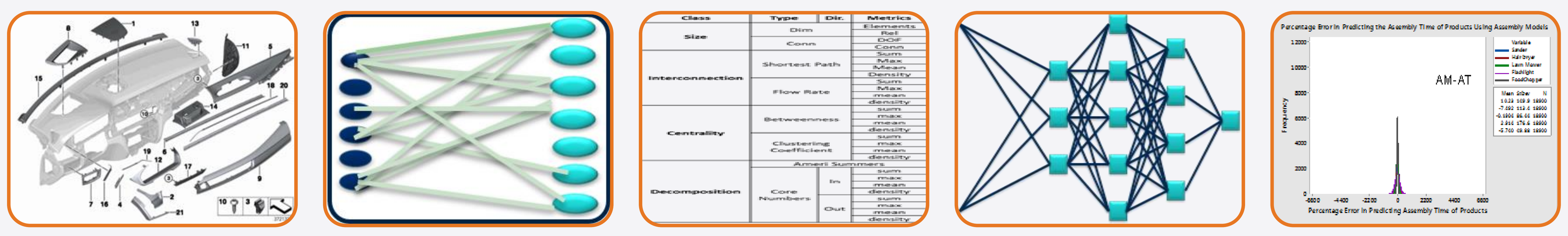
1. Overview

Assembly quality control has been an area of concern for manufacturing companies due to increasing product complexity. With computational resources that engineers did not have in the past, certain predictive models have begun to help designers and engineers make better decisions earlier in the design process to avoid unwanted waste and defects in production. This research aims to predict assembly quality defects with assembly models.

2. Current Practices

Currently, assembly models are being used to predict market value and assembly time. This methodology has been successful and there seems to be potential to grow the uses beyond assembly time and market value. [1]

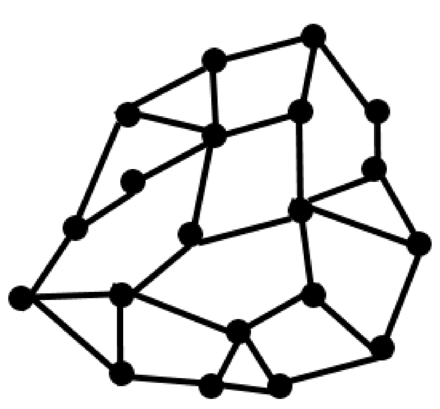


Collect assembly models of and related target data for existing products and systems	Convert assembly models to Bi-Partite graphs	Convert assembly Bi-Partite graphs to complexity vectors	Train 189 Artificial Neural Network (ANN) architectures with complexity vectors and target data	Test similar products and systems to predict target data

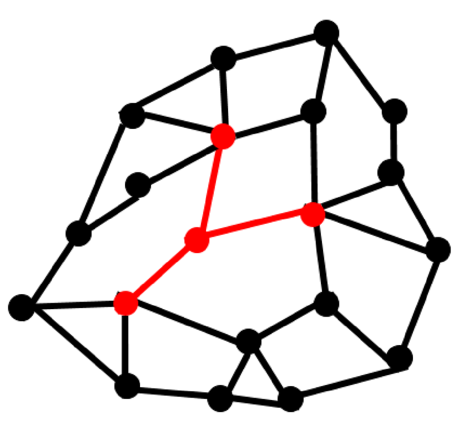
3. Changes to Experimental Design

Two Major Changes in the Experimental Design Exist

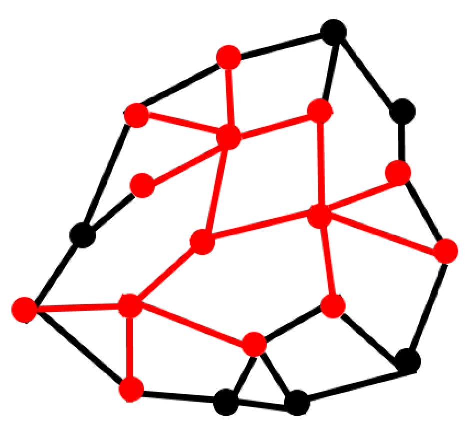
1. Isolating Part Specific Bi-Partite Graphs within a system instead of using the entire system.
   - Since the motivation is to predict assembly quality issues, the specific parts must be individualized instead of treated as one system. These graphs are done using First and Second Order connections.



Entire Bi-Partite Graph

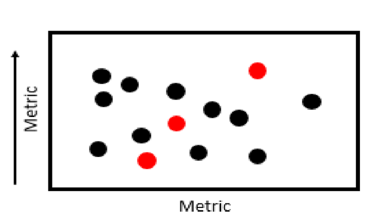


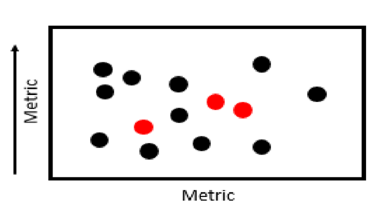
First Order Connections



Second Order Connections

2. Quality Defects during Assembly Process as Target Values
   - Previous experiments have used assembly times and market value. This research will use Assembly Quality Defects calculated as a count of the defects and the repair time. The six categories of defect include Total, Gap, Missing, Loose, Wrong, and Miscellaneous
3. Selection of training sets and tests sets for improving prediction

Extrapolating: 

Interpolating: 

7. Conclusions

There is an opportunity in manufacturing and design to explore the possibilities of data mining and machine learning tools. The results from initial tests performed are unsatisfactory but incremental improvement has been observed. There are numerous untapped resources within these fields to create more accurate, more helpful, faster models that can help in all areas of manufacturing.

4. Current Progress

- Identified 23 parts of an automobile with corresponding defect values
- Generated Bi-Partite graphs and complexity metrics for all parts
- Completed tests for randomized training and test groups and selected training and test groups.
  - 125 tests completed and 105 more scheduled
- Explored different approaches on error calculations
- Explored part classification based on the defect values for parts

5. Results

Results from Random Grouping Prediction

		First Order					Second Order				
		Test Part 1	Test Part 2	Test Part 3	Test Part 4	Test Part 5	Test Part 1	Test Part 2	Test Part 3	Test Part 4	Test Part 5
Target 1	Target	16	111	0.001	3750	31	16	111	0.001	3750	31
	Predicted	519.36	519.36	357.19	187.04	395.93	452.05	264.61	292.05	528.05	77.67
	Error										
Target 2	Target	2	13	6	21	2	2	13	6	21	2
	Predicted	47.05	47.05	23.25	76.96	75.11	103.31	85.17	13.48	27.11	13.26
	Error										
Target 3	Target	53	131	35	3932	34	53	131	35	3932	34
	Predicted	687.82	687.82	529.13	426.72	564.12	671.29	436.90	386.85	669.70	164.93
	Error										
Target 4	Target	35	7	29	128	1	35	7	29	128	1
	Predicted	254.09	254.09	226.20	50.17	105.37	289.24	222.43	72.63	120.04	37.10
	Error										

Green = < 100% Error
Yellow = 100% to 200% Error
Red = > 200% Error

First Order: 20 predictions (1 green, 1 yellow and 18 red)
Second Order: 20 predictions (4 green, 0 yellow and 16 red)

Results from Selected Set Prediction

		First Order					Second Order				
		Test Part 1	Test Part 2	Test Part 3	Test Part 4	Test Part 5	Test Part 1	Test Part 2	Test Part 3	Test Part 4	Test Part 5
Target 1	Target	31	640	51	1506	164	31	640	51	1506	164
	Predicted	-7.06	442.54	77.05	226.68	-136.58	1231.19	503.25	-279.66	888.95	128.96
	Error										
Target 2	Target	2	95	0	4	15	2	95	0	4	15
	Predicted	1.22	11.20	0.16	-2.94	2.93	280.66	0.79	29.87	148.37	153.47
	Error										
Target 3	Target	34	1248	55	1941	265	34	1248	55	1941	265
	Predicted	514.62	87.05	443.55	656.28	208.50	1969.48	508.47	-229.66	1292.14	452.94
	Error										
Target 4	Target	1	513	4	431	84	1	513	4	431	84
	Predicted	130.60	47.35	68.74	105.52	65.08	-54.70	102.24	-29.56	-9.74	-27.45
	Error										

Green = < 100% Error
Yellow = 100% to 200% Error
Red = > 200% Error

First Order: 20 predictions (9 green, 3 yellow and 8 red)
Second Order: 20 predictions (7 green, 2 yellow and 11 red)

6. Future Plans

Moving forward, the work aims to modify and improve the results through different objectives.

1. Include and compare Third Order Bi-Partite Graphs
2. Perform a Sensitivity Analysis on the 29 complexity metrics to develop a greater understanding of the predictive models behavior
   - Potentially uncover a discrete, non-linear relationship within the data
   - Reduce the number of metrics in hopes of further simplifying the ANNs
3. Compare the results of the 189 Different Neural Network Architectures for trends and potentially reducing the population of architectures
4. Gather more parts from the same vehicle and begin to collect data and parts from separate vehicles

References

[1] Sensitivity and Precision Analysis of the Graph Complexity Connectivity Method, Sudarshan Sridhar.

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