Comparison of Graph Generation Methods for Structural Complexity Based Assembly Time Estimation

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This paper compares two different methods of graph generation for input into the complexity connectivity method to estimate the assembly time of a product. The complexity connectivity method builds predictive models for assembly time based on 29 complexity metrics applied to the product graphs. Previously, the part connection graph was manually created, but recently the assembly mate method and the interference detection method have introduced new automated tools for creating the part connectivity graphs. These graph generation methods are compared on their ability to predict the assembly time of multiple products. For this research, eleven consumers products are used to train an artificial neural network and three products are reserved for testing. The results indicate that both the assembly mate method and the interference detection method can create connectivity graphs that predict the assembly time of a product to within 45% of the target time. The interference detection method showed less variability than the assembly mate method in the time estimations. The assembly mate method is limited to only solidworks assembly files, while the interference detection method is more flexible and can operate on different file formats including IGES, STEP, and Parasolid. Overall, both of the graph generation methods provide a suitable automated tool to form the connectivity graph, but the interference detection method provides less variance in predicting the assembly time and is more flexible in terms of file types that can be used.
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1 Assembly Time Estimation Methods

Design for assembly (DFA) focuses on improving product design with an emphasis on improving the assemblability as measured by time, ease, or cost [1–10]. To compare the expected benefit of implementing DFA guidelines, several methods have been developed to estimate the assembly time of a product [3,11,12]. In general, these methods are used to compare designs on a relative scale; comparing a design product before and after DFA guidelines have been applied.

1.1 Boothroyd and Dewhurst Method. The Boothroyd and Dewhurst (B&D) assembly time estimation method is empirically developed based on extensive data collected from assembly plants [3]. The Boothroyd and Dewhurst assembly time estimation method requires the user to manually input handling and insertion information into a table. Each part would receive a handling code and insertion code based on categories used to describe the part [3]. For instance, the handling code would depend on part information such as length, thickness, part symmetry, and handling difficulties. After a handling code and insertion code is determined for each part in the assembly, a handling time and insertion time can then be found in the B&D assembly time charts. The sum of the handling time and the insertion time for each part is the estimated assembly time for the part. The sum of all estimated assembly times for each part results in the overall assembly time of the product.

Recently, Boothroyd and Dewhurst Inc. has released a software to help automate the assembly time estimation[1]. The software supports the user by providing a graphical user interface (GUI) to input the part information and will retrieve the associated handling and insertion times. One limitation of the B&D method is the time required to analyze a product even with the extensive training (which is a service that can be purchased). The time required to analyze product using the B&D method motivated the need for an automated assembly time estimation method [13]. Regardless of the limitations, this method appears to be the most prevalent in the literature and in industrial application.

1.2 Complexity Connectivity Method. The complexity connectivity method (CCM) uses a complexity vector composed of 29 graph based complexity metrics to estimate the assembly time of a product [14,15]. The complexity metrics are calculated based on the bipartite representation of a product (see Fig. 1). For brevity, the discussion, details and calculations of the complexity metrics are not included in this paper but can be found in previous literature [14,15].

Initially, the CCM used a linear regression model to create a relationship between the complexity metrics and the assembly time of a product [12]. To improve the predictive ability of the connectivity complexity method, the relationship model evolved from a linear regression to an artificial neural network (ANN)

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[1] http://www.dfma.com/ accessed 12/2017/2012

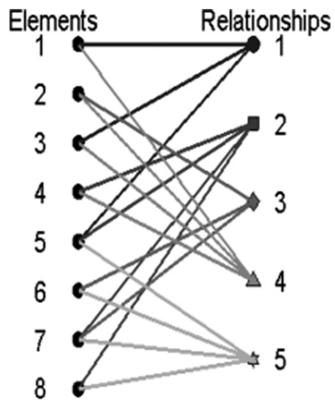


Fig. 1 Bipartite graph [15]

[16]. The ANN complexity connectivity method (ANN-CCM) is trained using the complexity vector of a product (with known assembly time) as the input into the ANN and the known assembly time is the training target. The ANN is used as a data mining tool to find the relationship between the complexity vector and the known assembly times. The use of the ANN was shown to improve the predictive ability of the method; however, the manual bipartite graph generation was still time consuming and inherently subjective due to manual creation [13,16]. To further improve the CCM, an automated graph generation method is needed.

2 Complexity Graph Generation

The original CCM manually created the bipartite graph, but due to the extensive effort required to create the bipartite graphs, recent research has motivated the need for automated graph generation. The next improvement to the complexity connectivity method was the assembly mate method, an automated graph generation tool [14].

This paper will focus on the comparison of two graph generation methods used for creating the bipartite graph needed to calculate the complexity metrics for estimating the assembly time of a product. The two methods that are evaluated are the interference detection method (IDM) and the assembly mate method (AMM). Both methods are programmed in C++ using Visual Studio 2010, SolidWorks 2011, and the SolidWorks 2011 Application Programming Interface (API).

2.1 Assembly Mate Method. The AMM uses SolidWorks (SW) assembly mate information to create the connectivity graphs needed for the complexity connectivity method. The mates in SW are the relationship that a user specifies to assemble a part onto another part or assembly such as a coincident mate or concentric mate (see Fig. 2 for additional standard SW mate types).

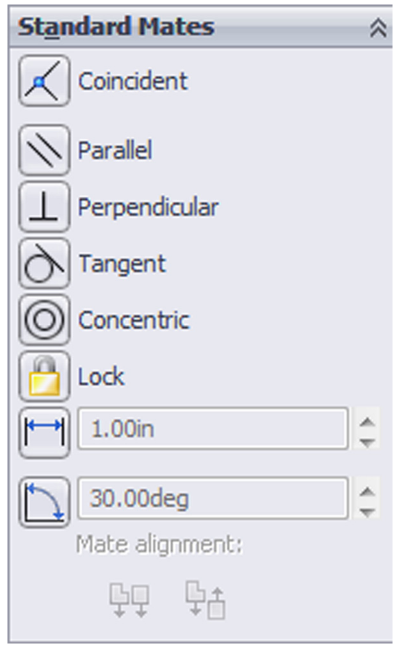


Fig. 2 Standard solidworks mates

The mate creates a relationship between two components and SolidWorks retains this relationship information as a parent-child relationship. For example, consider a block with a circular hole and a pin (see Fig. 3).

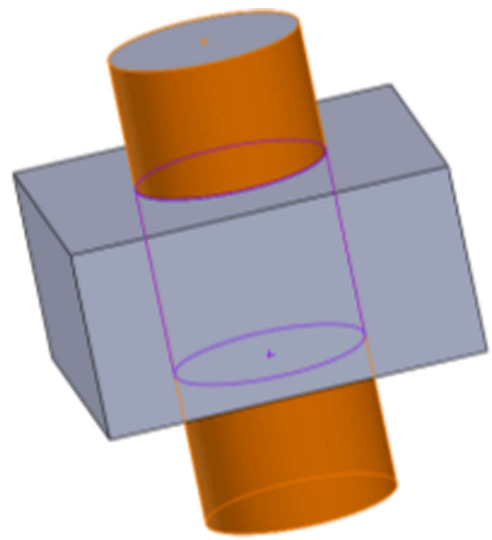


Fig. 3 Block and pin assembly

The automated graph generation tool uses the "Parent/Child Relationship" information to find the connections between parts in the assembly (see Fig. 4) [14]. For example, the concentric relationship exists between the "Block-1" and the "Pin-1" and is identified in the child parent relationship window (see Fig. 4).

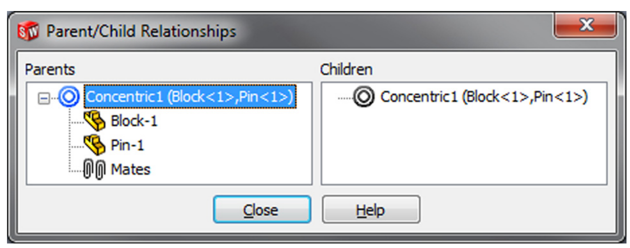


Fig. 4 parent-child relationship

The assembly mate method iterates through every mate in the assembly to create a list of parent child relationships. This list is output as a text file to be used as the input to find the complexity vector for the assembly.

2.2 Interference Detection Method. The AMM provided an automated method for creating the complexity graphs based on the mates used to create an assembly. Another method for generating the complexity graphs has been developed that uses part interference to create the complexity graphs.

The IDM utilizes the interference detection tool in SW to determine the connectivity between parts (see Fig. 5). The interference detection tool detects overlapping part geometry between any two parts in an assembly. Furthermore, the interference detection tool

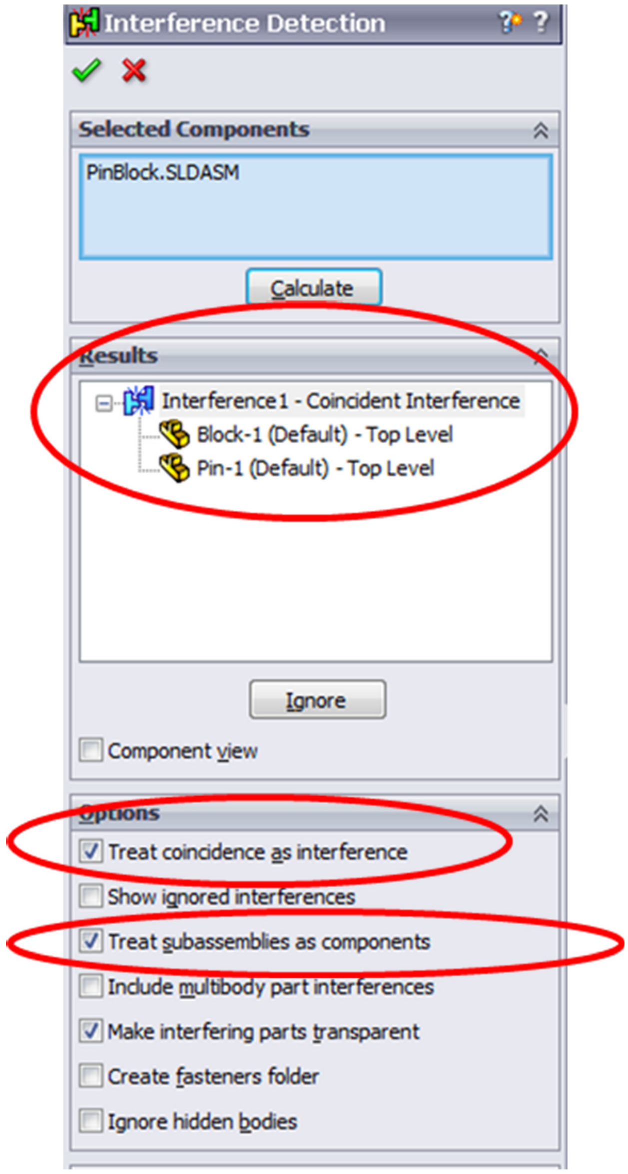


Fig. 5 Interference detection tool

has additional options that are selected to "treat coincidence as interference" and to "treat subassemblies as components." The treat coincidence as interference allows for situations when an interfering part has the same nominal size as a part into which it fits or when a face of a part is coincident with another. For example, in block and pin assembly, the nominal size of the pin is the same as the size of the hole in the block. The interference detection tool detects this as interference when the option is enabled (see Fig. 5).

When a subassembly is placed into an assembly in SW, the entire subassembly is treated as one body or part. The treat subassemblies as components option, in the interference detection tool, allow the tool to look at each part in the subassembly separately. The interference detection tool was run on the same block and pin assembly from earlier. The results indicate that a connection was detected between the block and the pin (see Fig. 5). Each portion of the part that is found to interfere is colored/shaded in the model (see Fig. 6).

The interference detection algorithm is implemented in C++ using the SW API to find all interfering parts of the assembly and export a text file containing the part connection information. The interference detection tool may be run directly from the SW

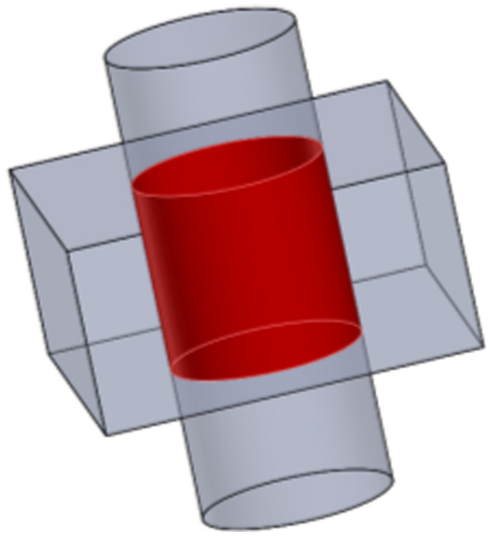


Fig. 6 Block and pin detection tool result

menu, by accessing the evaluate tab in an assembly file. The manual use of the interference detection tool results in a list of interferences in the SW GUI (see Fig. 5).

The CCM has been improved towards developing a fully automated assembly time estimation tool. A summary of the different iterations that have been undertaken as well as information regarding the source of training product times and models can be found in Table 1.

2.3 Demonstration of Graph Generation Methods. To compare the two methods, a demonstration of the analysis on an ink pen is provided (see Fig. 7)

The pen was chosen for demonstration due to a limited complexity and number of part. This example does not demonstrate the full ability of the methods to create graphs for more complex products as used in the comparison in Sec. 30 of this paper. The parts of the pen include a grip body (1), rubber grip (2), spring (3), ink body (4) indexer (5), press button (6), and body (7) (see Fig. 8).

2.3.1 Assembly Mate Graph Generation Method. The AMM was used to find the part connections for the ink pen. The AMM outputs a text file with a part in the left column and the part it is connected to in the right column (see Table 2). For example, the first row indicates that the "Grip Body" is connected to the "Rubber Grip" and the second row indicates that the Grip Body is also connected to the "Ink Body"

For visual representation the information resulting from the AMM is represented as a bipartite graph (see Fig. 9). The "Front Plane" is included in the list of physical part connections. The AMM retrieves all of the assembly mates used to create the model; therefore, if a part is assembled to a reference plane or a reference axis, the reference features are also included as part of the connection graph.

2.3.2 Interference Detection Graph Method. The IDM was then used to generate the connectivity graphs for the ink pen. Once again, the output from the IDM is a text file indicating the connectivity between parts (see Table 3).

For comparison purposes with the AMM, the bipartite graph was also created for the IDM (see Fig. 10).

2.3.3 Ink Pen Assembly Time Estimation Comparison. The part connection graphs are used as the input to calculate the complexity vector. The complexity vector was calculated for the IDM and the AMM (see Table 4). For brevity, the specific calculations for each of the complexity metrics have been omitted [12,17].

Table 1 Summary of CCM progression

	CCM	ANN-CCM	AMM	IDM
Graph generation	Manual	Manual	Automated (CAD)	Automated (CAD)
Estimation tool	Linear regression	ANN	ANN	ANN
Training products	Consumer products and prototypes from industry sponsored projects	Automotive subsystems	Consumer products with models available	Consumer products from previous literature
Training assembly times	Boothroyd and Dewhurst	Industry specified	Boothroyd and Dewhurst	Boothroyd and Dewhurst
Supported file types	N/A	N/A	SW Assembly ONLY (*.asm;*.sldasm)	IGES (*.iges)Parasolid (*.x_t;)STEP (*.step)

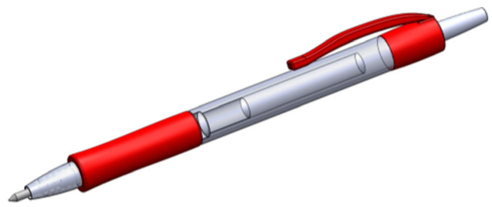


Fig. 7 Ink pen

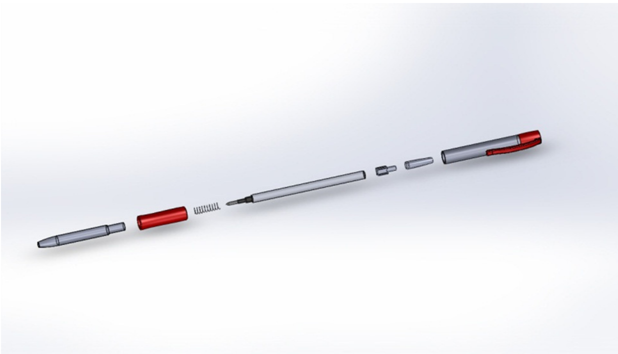


Fig. 8 Exploded view of ink pen

Table 2 Partially defined AMM

Grip body	Rubber grip
Grip body	Ink body
Spring	Rubber grip
Ink body	Indexer
Press button	Indexer
Grip body	Body
Grip body	Rubber grip
Spring	Grip body
Ink body	Grip body
Press button	Body
Press button	Indexer
Rubber grip	Body

Each of the complexity metrics, developed by the respective graph generation methods, was used as input training vectors to the ANN. At this point, the complexity metrics could be used to estimate an assembly time using a previously trained ANN. However, since the pen was used in the training of the ANN for this paper, it was omitted from testing of the predictive ability of the neural network. The comparison of performance of the two graph generation methods is reserved for products which were not included in the ANN training.

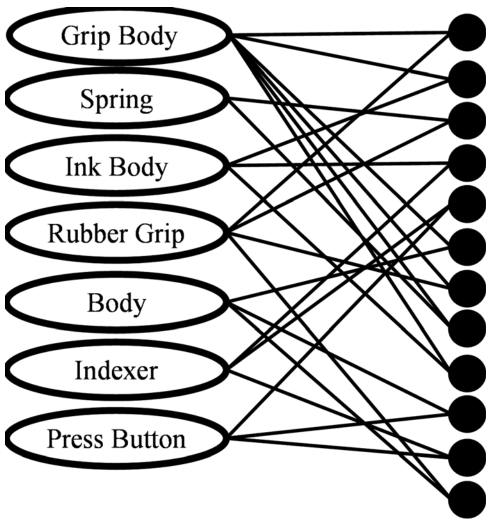


Fig. 9 AMM bipartite graph of the ink pen

Table 3 Part connections for IDM

Grip body	Rubber grip
Grip body	Ink body
Grip Body	Spring
Rubber grip	Body
Press button	Indexer
Press button	Indexer
Press button	Indexer
Press button	Indexer
Press button	Body
Spring	Ink body

3 Performance Comparison of Methods

To compare the performance of the methods a total of fourteen household products (for which CAD models could be obtained or created) were chosen for analysis. From the 14 products to be used in the analysis, 11 products were used to train the ANN and three products were withheld for testing. A summary of the products used for testing and training along with an image of each is presented in Table 5.

3.1 Assembly Time Estimation Comparison. The connectivity graph for the 11 training products was obtained using both the AMM and the IDM methods and used to find the complexity metrics for each part. The complexity metrics for each respective method was obtained and was used as the input for training of the ANN. The target time for each of the products was calculated using the manual Boothroyd and Dewhurst assembly time estimation charts [3].

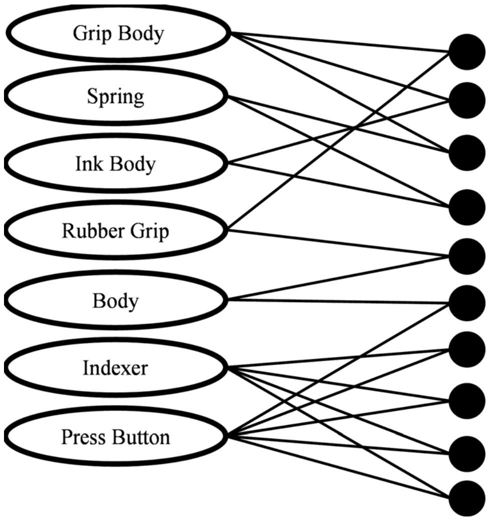


Fig. 10 IDM bipartite graph of the ink pen

The connectivity graphs and complexity vectors for the test products were then generated using each of the graph generation methods. The previously trained ANNs were then used as a prediction tool to estimate the assembly time of the test products. Each ANN is composed of 189 architectures resulting from fifteen neurons and one hidden layer [14]. Due to the stochastic nature of the ANN, each architecture results in 100 prediction estimates, resulting in 18,900 predicted assembly time data points for each product. The average time of all of the results of an ANN is the average predicted assembly time for the product (see Table 6, Fig. 11). The number of architectures as well as repetitions for each architecture may be reduced to decrease computational effort, however, the focus of this research is not ANN design but strictly the application of the predictive ability of the ANN as a tool, therefore ANN design is reserved for future work [18–20].

To compare the predictive ability of each of the graph generation methods, the mean percentage error (MPE) was calculated for each neural network. The MPE is calculated as the following:

$$MPE = \frac{1}{n}\sum_{1}^{n}\frac{P_i - T}{T}, \quad where \quad i = 1, 2, 3, \ldots, n \tag{1}$$

where n is number of observations, T is target time, and P is predicted time

To compare the mean percent error values a 2 sample t-test was conducted. Based on the central limit theorem, the sample size is large enough to assume a normal distribution and therefore a two sample t-test with unknown variances is appropriate [21,22].

The hypothesis test was used to test if the mean average error of the IDM was statistically different than that of the AMM. The confidence interval used for this test was 95%.

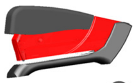
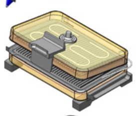
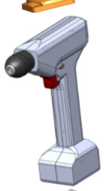
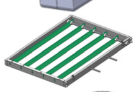
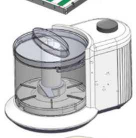
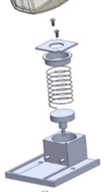
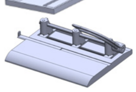
$$\mathrm{H}_0 \sim \mu_0 = \mu_1$$
$$\mathrm{H}_1 \sim \mu_0 \neq \mu_1$$

The results indicate a p-value less than 0.05 providing evidence to reject the null hypothesis. The mean value of the AMM is −0.019 and the mean value of the IDM is 0.156. The t-test suggests that the mean percent error values of assembly time are not equal (see Table 6). While there is statistically significant evidence that the means are not equal practically the difference in the means are not very different. Graphically, the mean percentage error of the IDM

Table 4 Complexity metrics for ink pen

					G2 Pen	
				Product name	IDM	AMM
Complexity Metrics	Size	Dim		Elements	7.00	7.00
				Relations	10.00	12.00
		Conn		DOF	10.00	12.00
				Connections.	20.00	24.00
	Interconnection	Shortest path		Sum	102.00	72.00
				Max	5.00	3.00
				Mean	2.43	1.71
				Density	0.24	0.14
		Flow rate		Sum	54.00	124.00
				Max	4.00	6.00
				Mean	1.10	2.53
				Density	0.11	0.21
	Centrality	Betweenness		Sum	60.00	30.00
				Max	18.00	11.00
				Mean	8.57	4.29
				Density	0.86	0.36
		Clustering coefficient		Sum	2.33	2.33
				Max	1.00	1.00
				Mean	0.33	0.33
				Density	0.03	0.03
			Ameri summers		20.00	28.00
	Decomposition	Core numbers	In	Sum	10.00	14.00
				Max	2.00	2.00
				Mean	1.43	2.00
				Density	0.14	0.17
			Out	Sum	10.00	14.00
				Max	2.00	2.00
				Mean	1.43	2.00
				Density	0.14	0.17

Table 5 CAD models used for training and testing

Product name	Training/ testing	CAD model image	Source [14]
Stapler	Testing		GICL website
Flashlight	Testing		SW 3D content
Blender	Testing		Reverse engineered
Ink pen	Training	See Fig. 7	Reverse engineered
Pencil compass	Training		Reverse engineered
Electric grill	Training		SW 3D content
Solar yard light	Training		Reverse engineered
Bench vise	Training		Reverse engineered
Electric drill	Training		Reverse engineered
Shift frame	Training		OEM
Food chopper	Training		Reverse engineered
Computer mouse	Training		Reverse engineered
Piston	Training		Reverse engineered
3- Hole punch	Training		Reverse engineered

and the AMM are similar (see Fig. 12). The graphical depiction, however, does suggest that while the means are similar, the variance observed with the AMM method is greater than that observed with the IDM. The graphical evidence supports that both methods are relatively accurate in estimating assembly time, but the IDM method produces less variance.

Table 6 Predicted assembly times of test products

	Target time	AMM Average predicted time	IDM Average predicted time
Stapler	123.51	115.84	89.98
Flashlight	75.40	107.65	65.96
Blender	263.21	290.40	352.09

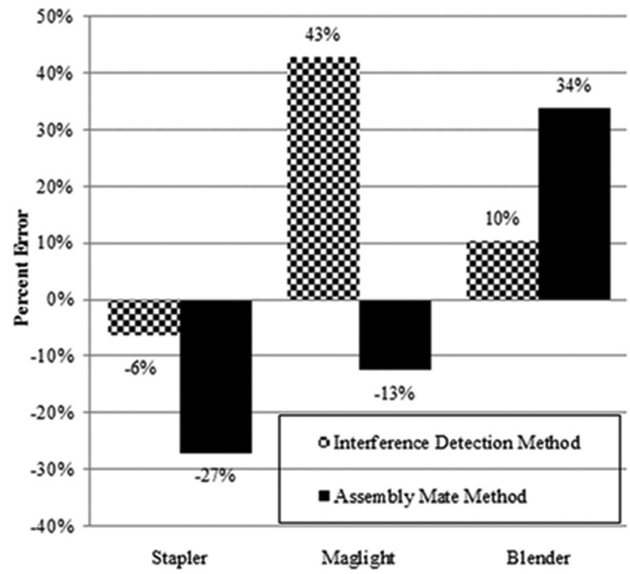


Fig. 11 Mean percent error of test products

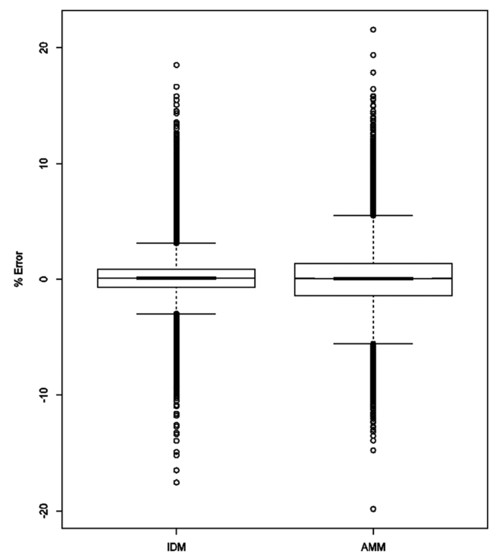


Fig. 12 Mean percent error comparison of AMM and IDM

3.2 Analysis Time. The time required to train, load, and run an ANN for the assembly time estimation using both methods is approximately equal since both methods input the same amount and type of information. The required input for the ANN is simply the complexity vector. However, the time required to generate the connectivity graph based on a CAD model is significantly less for the AMM compared to the IDM (see Table 7). The significant

Table 7 Graph generation time comparison

	AMM			IDM		
	Graph generation time (s)	No. of elements	No. of relations	Graph generation time (s)	No. of elements	No. of relations
Flashlight	5	18	36	30	16	55
Stapler	1	14	27	43	14	20
Blender	1	48	105	97	43	129

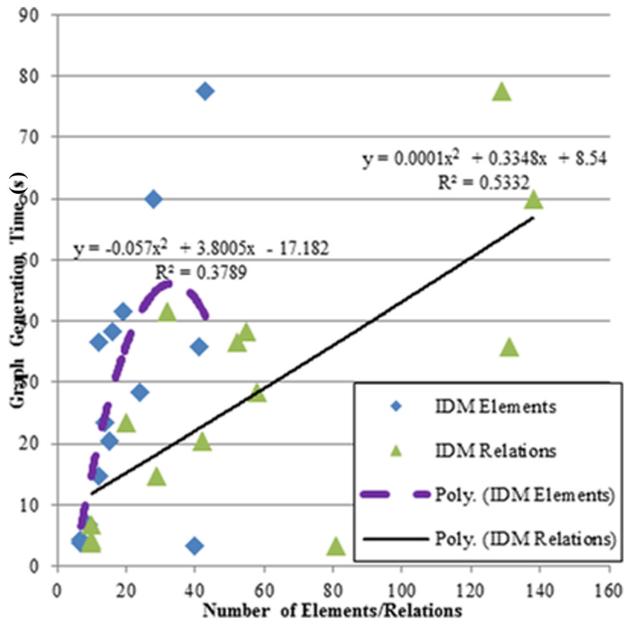


Fig. 13 Graph generation times for IDM

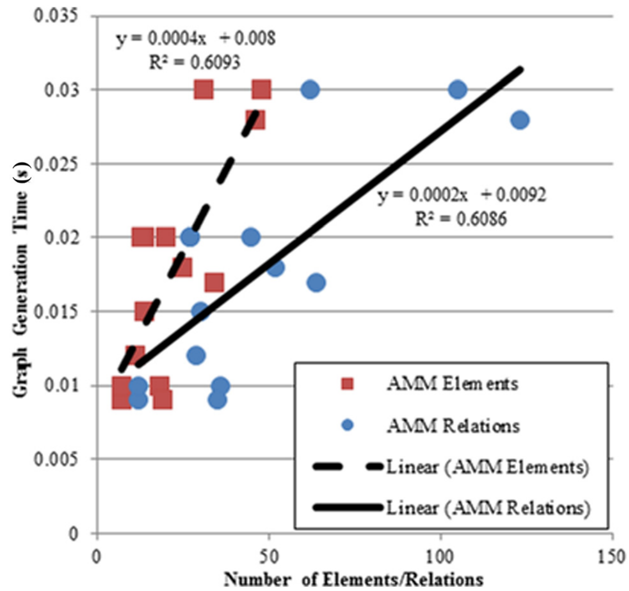


Fig. 14 Graph generation times for AMM

increase in analysis time for the IDM can be attributed to the algorithm complexity. The IDM must compare each part in the assembly to every other part to find interference, resulting in a computational complexity of $O(N^2)$. The AMM simply retrieves the created mates list to generate the part connectivity graph, resulting in a computational complexity of O(N).

The time to generate the graph for the fourteen consumer products (see Table 5) was recorded to compare the theoretical complexities of the algorithms to the actual implementation. The graph generation time for the AMM and the IDM are plotted with respect to the number of elements and the number of relations (see Figs. 13 and 14). Note that the number of elements and relations identified by each method are not identical and are not equal to the number of parts, therefore, each graph generation time is plotted with respect to the number of elements and relations identified by the respective method.

Theoretically, the IDM algorithm is polynomial, however, the applied results of the graph generation times initially indicate that the polynomial fit based on number of elements or relations alone is not sufficient. A number of factors could be considered to be the cause of the discrepancy between the theoretical and applied graph generation times. First of all, the sample size is not sufficiently large enough to draw complete conclusions. A set of products with a larger range in number of parts and relations would need to be tested to further support the actual relationship between graph generation time and number of elements or relations. Another possible contribution to the discrepancy is the complexity of the part topology. To find the interference of a part with multiple edges and faces requires greater computation than a part with a simple geometry. This, however, will also need to be tested further. To do this, a study would need to be conducted in which an assembly composed of parts with simple geometries is compared to a similar assembly in which the geometry of the parts is changed, but the interfering components should remain the same. This is not the focus of this research and is reserved for future work.

The AMM reveals a relatively linear trend with the increase in elements or relations having a minimal effect on the graph generation time (see Fig. 14). The AMM is traversing a list that has been created by the SW program during the assembly modeling, and then writing this information to a text file. For this reason, the applied results generally follow the trend expected from the theoretical evaluation. While the results generally follow the expected trends, the sample size and variation in number of elements and relations is still limited and requires additional testing to support these claims. Future work includes investigation into the complexities of the IDM and AMM algorithms to try to decrease the computation effort required but is not the focus of this research and is reserved for future work.

3.3 Supported CAD File Types. One major advantage of the IDM over the AMM is the ability to handle additional file types other than SW assembly file. The AMM is dependent on having a SW assembly file from which to retrieve assembly mates from. The IDM is able to create the connectivity graph of many different native file formats and has been tested on the following: SW assembly file (*.sldasm), IGES (*.iges), parasolid(*.x_t), and STEP (*.step;*.stp) (summarized in Table 8). The STL file type is the only tested file type that is not currently supported by the IDM. The STL file is limited because SW imports the entire assembly as one body and with only one body there is no interference. This may be improved in the future to support STL files if an assembly can be imported as separate bodies.

While the IDM can support multiple file types, SW is still required as the add-in utilizing the interference detection tools

Table 8 IDM supported file types

File type	File type extension	Supported
SolidWorks assembly	*.asm;*.sldasm	✓
IGES	*.iges; *.igs	✓
Parasolid	*.x_t;*.x_b;*.xmt_txt;*.xmt_bin	✓
STEP	*.step;*.stp	✓
STL	*.stl,	✗

Table 9 Part connections for AMM

Grip body	Rubber grip
Grip body	Ink body
Spring	Rubber grip
Ink body	Indexer
Press button	Indexer
Grip body	Body
Grip body	Rubber grip
Spring	Grip body
Ink body	Grip body
Press button	Body
Press button	Indexer
Rubber grip	Body
Rubber grip	Front plane
Spring	Front plane
Ink body	Front plane
Press button	Front plane
Indexer	Front plane
Body	Front plane

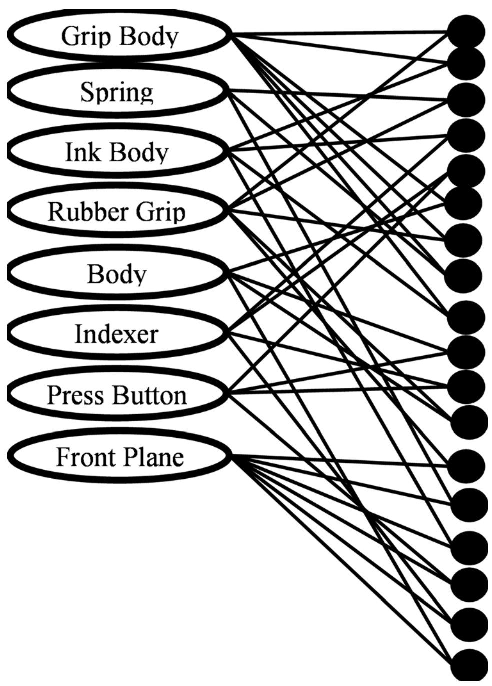


Fig. 15 AMM bipartite graph of fully defined ink pen

built using the SW API. However, the benefit is files can be saved into a standard CAD file format from other CAD systems and imported into SW to run the IDM.

3.4 Modeling Dependency. When creating a solid model, there are numerous ways a designer could model the product. The actual technique used to model the part geometry may vary by designer, but this is out of scope of this research. On the other hand, given a set of parts, different designers will mate them in different ways to form the assembly. For instance, based on the ink pen example from earlier, an alternate designer may mate multiple parts to a reference plane. Furthermore, a designer may choose to limit the motion of all of the parts in the assembly to create a fully defined assembly in which all parts have zero degrees of freedom. This situation would result in an entirely different connectivity graph based on the AMM. Since the AMM utilizes the mates from the assembly model to create the connection graph, all reference items which are used to mate the assembly are also included as entities (see Table 9).

These added relations increase the complexity of the connectivity graph and therefore also generate a different complexity vector and bipartite graph resulting in a different assembly time estimate (see Fig. 15).

Since the IDM is based on location of the parts in the modeling space, the connectivity graph is not dependent on the modeling style of the designer, but strictly on the location of the parts in the assembly space.

Table 10 Performance Comparison of IDM and AMM

Performance metric	IDM	AMM	Section	Comments
Accuracy	✓	✓	3.2	Both methods were relatively accurate, but statistically AMM had the advantage.
Modeler dependency	✓		3.4	The IDM is based on part location in the assembly space as opposed to the AMM which is based on assembly mates chosen by the designer. The assembly mates used may change based on the designer creating the model.
File format dependency	✓		3.3	AMM requires SW Assembly Files, but IDM can use a number of standard CAD file types
Graph generation time		✓	3.2	The complexity of the AMM algorithm is simpler than the IDM resulting in a much faster graph generation time

4 Conclusions and Future Work

The IDM and the AMM both provide automated tools to generate the connectivity graph of an assembly. This graph is used as the input into the connectivity complexity method and provides an automated method of estimating the assembly time of a product based on a CAD model.

Both methods are able to generate connectivity graphs which are used with the connectivity complexity method to predict a relatively accurate assembly time. However, each method has its own advantages and disadvantages. Although both methods were able to predict the assembly times of the products, the IDM method had less variance in the time estimates. The IDM can handle a multitude of standard CAD formats, while the AMM is restricted to only SolidWorks assembly files. The time required to form the connection graphs is much shorter for the AMM compared to the IDM due to the program complexity. A summary of the performance characteristics for each method is shown in Table 10.

One major limitation to the current research in this area is number of products for training and testing. The current research is limited by the number of products due to the large amount of time needed to manually create product models and determine assembly times using the Boothroyd and Dewhurst assembly time charts. A larger set of product models and assembly times are needed to further validate the method.

Additionally, the construct validity of the method needs to be tested to determine if the results found from test products with manually estimated assembly times can be used to predict actual assembly times measured from current manufacturing process. Current collaboration with a local original equipment manufacturer is underway to validate this work with industry products and actual assembly times.

Future research directions include significance testing of the complexity vector to determine if the 29 complexity metrics currently being used are all needed for accurate assembly time estimation or if even more metrics may provide better estimates. The current research provides additional milestones in an ultimate goal of a fully automated assembly time estimation method.

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