Complexity Connectivity Metrics – Predicting Assembly Times with Low Fidelity Assembly CAD Models

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Abstract. Expanding on previous work to predict assembly times from detailed assembly models, low fidelity part models are used in a series of predictive performance experiments. Results reveal that this tool can predict the assembly time of a product to within 40% of the target "as built" time using a high fidelity neural network and a low fidelity CAD model. The tool is based on structural complexity, representing the assembly graph as complexity vector of 29 metrics. The graphs are automatically compiled from examining part proximity (interference checks) regardless of the choice of mating constraints used in the modeling. A neural network is then used to build a relationship between the complexity vector (input) and the assembly time (output). Low-fidelity models can be used to predict assembly times, thereby supporting earlier inclusion of design for assembly methods in the design process.

Keywords: Design for Assembly, Assembly Time Estimation, DFA

1 Motivation for Time Estimation

Design for Assembly (DFA) is a design method used in industry to improve the assemblability of a product with the ultimate goal of reducing manufacturing costs. With increasing manufacturing costs, an interest in DFA has emerged due to the assembly phase in product development accounting for approximately 50% of the manufacturing time and 20% of the manufacturing cost [1–8]. Furthermore, approximately 70% of the total product cost is determined during the early stages of design, motivating the need for DFA tools that can support product development throughout the design process [9, 10].

Assembly time estimation tools, within the larger design for assembly method, have been developed for predicting the assembly time of a product [5, 8, 11]. Time estimate tools do not support assembly time estimation in the early stages of design as detailed information about the parts, assembly sequence, and assembly structure are required. This information is often not determined until the embodiment or detail design phase of the design process. The majority of these assembly time estimation tools are used primarily to estimate the assembly benefit of a design change to an existing product. This paper focuses on the development of an extended complexity

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connectivity assembly time estimation [12–14] method based on information retrieved from low fidelity CAD models in the conceptual design phase.

1.1 Connectivity Complexity Method

The term complexity is used in many disciplines all with different interpretations of the definition [15–17]. For this research, the term complexity will be used to describe amount of information required to describe a system comprised of more than one component [15, 18]. Previous research developed a set of complexity metrics to capture the connectedness of parts within a system [12, 14, 19]. The connectivity method uses the complexity metrics as the input vector to a historical-based prediction model to estimate assembly times of a product [12–14]. The complexity connectivity method uses 29 graph-based complexity metrics of an assembly [14, 19].

2 Low Fidelity CAD Model Assembly Time Estimate: The Experiment

Previous work has focused on estimating assembly times from detailed component and assembly models. This work evaluates the potential of using components represented at lower levels of detail (conceptual models or low-fidelity models). While the exact dimensions and features of the components are not known, the general system architecture and layout is captured [20]. The form of the individual components are developed throughout the design process to create a completed CAD model with working drawings in the detailed design stage [20]. For clarity, low-fidelity models are those that are found in conceptual design and high-fidelity models are found in detailed design phases.

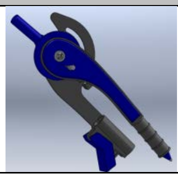
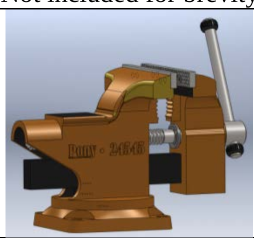
This experiment explores the use a modified complexity connectivity method to estimate the assembly time of models in the conceptual design phase. The estimated assembly time of the conceptual models is compared to the estimated assembly time of the complete models using the same modified complexity connectivity method. The following research questions are answered:

- What is the predictive power of ANN trained on detailed models to predict detailed models?
- What is the predictive power of ANN trained on detailed models to predict low fidelity models?
- What is the predictive power of ANN trained on low fidelity models to predict low fidelity models?
- What is the predictive power of ANN trained on low fidelity to predict high fidelity?

2.1 Set of Models

The experiment used a total of thirteen products (**Table 1**) to compare the estimated assembly time of high-fidelity models and low-fidelity models. The models were used in previous work and were created by multiple designers by physically reverse engineering existing products or downloading models from the public domain [13]. The last three models are withheld for testing purposes.

Table 1. Products Used in Training and Testingt

Common Name	Training/Testing	CAD Model Image
Stapler	Testing	Not included for brevity
Flash Light	Testing	
Ink Pen	Testing	Not included for brevity
Pencil Compass	Training	
Indoor Electric Grill	Training	See **Fig. 1**
Solar Yard Light	Training	Not included for brevity
Table Vise	Training	
Drill	Training	Not included for brevity
Shift Frame	Training	Not included for brevity
Vegetable Chopper	Training	Not included for brevity
Computer Mouse	Training	Not included for brevity
Piston Assembly	Training	Not included for brevity
3 Hole Punch	Training	Not included for brevity

2.2 Reducing Model Fidelity

Low-fidelity CAD models are difficult to define and are often not distinctly saved by the designer before they are evolved to more detailed higher fidelity models. For this work, the high-fidelity models were reduced in fidelity to represent low-fidelity models in the conceptual design phase.

To do this, each part included in an assembly model was reduced to its lowest level feature. In SolidWorks the feature tree stores the features used to create a part and the order in which those features were created. To decrease bias in the reduction of fidelity of the parts, the feature tree was reduced to the top level feature for each part. It should be noted that if a multiple designers create the same part, a different conceptual model may result. This uncertainty is not the focus of this research and is reserved for future work.

As an example, the first feature used to create a bolt is an extruded shaft (Boss-Extrude1). Next, a swept extrusion (Sweep1) is used to create the threads around the shaft of the bolt. An additional extrude (Boss-Extrude2) is used to create the bolt head and then an extruded cut (Cut-Extrude1) is used to cut the hex in the top of the bolt head. Starting from the bottom of the feature design tree, the Cut-Extrude1 is deleted, followed by Boss-Extrude2 and Sweep1 leaving only the initial extrude as an example of a conceptual model for a bolt (see **Table 2**).

Table 2. Reduction of Fidelity of a Bolt Complete Model to Create a Low Fidelity Model

			
Cut-Extrude1	Boss-Extrude2	Sweep1	Boss-Extrude1

This removes detail from the parts in the CAD model, leaving a low-fidelity model of the product simulating a model created in the conceptual phase of the design process. The indoor electric grill (**Fig. 1**) is similarly reduced from a detailed model to an assembly of the low-fidelity part models. Mating relationships may be lost in this transformation, precluding the use of previous graph generation tools [21]. Therefore, a mate-independent method for generating the connectivity graphs is used based on interference checks.

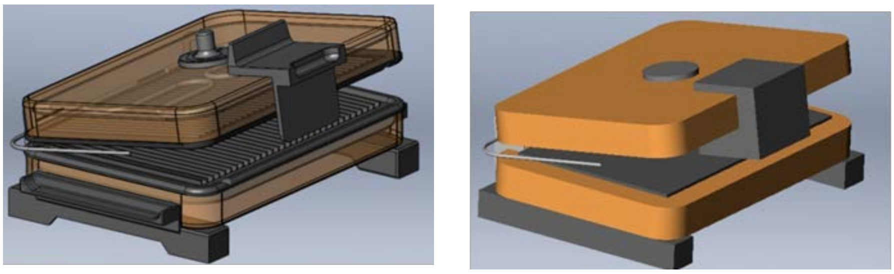


Fig. 1. Transformation of Electric Grill from High Fidelity Model to Low Fidelity Model

2.3 Artificial Neural Network Generation

The artificial neural network (ANN) used for this research is a supervised back propagation network [12, 13]. The ANN is trained by providing a set of input vectors and a set of target values. The ANN then creates a relationship between the input values and the target value. In this case, the complexity vector of 29 metrics is the input vector and the assembly time of the product will be used as the output. Once an ANN is trained, a new complexity metric is input and the ANN provides an assembly time.

2.4 Experimental Sets

Two separate neural networks are created and compared. The first ANN uses the complexity vector of the high-fidelity models as input and assembly times as the targets. The second ANN uses the complexity vectors of the low-fidelity models as the training inputs and the same assembly times as target times. This approach is used to test the ability to train a neural network to find a relationship between low-fidelity complexity vectors and product assembly times. Each ANN is used to predict the assembly time of a test data set (three products) using the high-fidelity and low-fidelity models. The experimental sets are summarized in **Table 3**.

Table 3. Experiment Design Sets

Set Number	ANN Trained on:	Test Set Type:
1	High Fidelity Models Vectors	High Fidelity Model Test Vector
2	High Fidelity Models Vectors	Low Fidelity Model Test Vectors
3	Low Fidelity Model Vectors	High Fidelity Model Test Vector
4	Low Fidelity Model Vectors	Low Fidelity Model Test Vectors

3 Conceptual Model Time Estimate Results

After the two ANN are trained, the input vectors are passed back in to the neural network to gain a qualitative assessment of ANN fit to the training set. One shortcoming with ANNs is the potential for overtraining, limiting the ability of the ANN to extrapolate to new data sets [22–24]. The percent error is calculated as the normalized difference from the target time (see Eqn. 1). A positive percent error indicates that the predicted time was greater than the target time, and a negative percent error indicates that the predicted time is less than the target time.

$$\text{Percent Error} = (\text{Predicted Time} - \text{Target Time})/\text{Target Time} \tag{1}$$

The ANNs are able to estimate the training set assembly times within 70% of the target time, but visually do not appear to be over fit to the training set data (see **Fig. 2**). Previous research offers techniques to prevent ANN over fit and improve performance of ANN by varying ANN parameters. As the focus of this paper is to demonstrate the potential to use ANN to predict assembly times of low-fidelity models, the improvement in design of the ANN itself is reserved for future work.

To test the performance of the two ANNs in predicting the assembly times, complexity vectors of three products (stapler, flash light, and ink pen) not used in the training are used for testing. For each of the test products the high fidelity and low fidelity graph complexity vectors were calculated and used as the input to both ANNs trained (high fidelity and low fidelity).

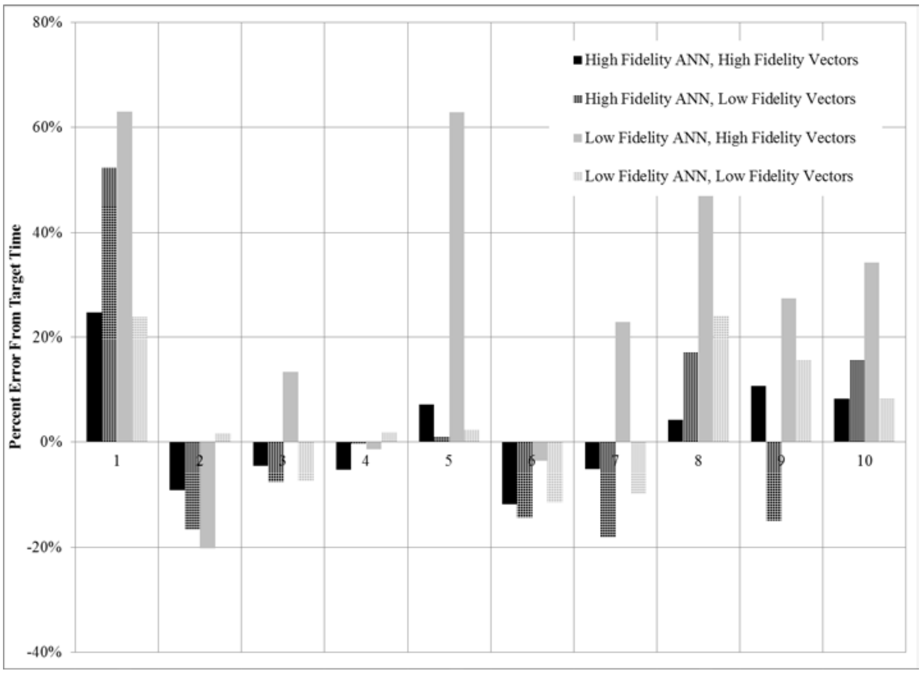


Fig. 2. Training Set Percent Error from Target Time

The target time, the predicted time, and the percent error for each of the three test cases are presented in **Table 4**. Each ANN predicted an assembly time greater than the target time for the test cases except for the high-fidelity ANN for the stapler. The test products varied in target assembly times from 34 seconds to 123 seconds. Additional test cases with a larger range of assembly times are needed to determine if the ANN time estimate accuracy is dependent on the assembly time or the complexity of the product being studied, but this is reserved for future work.

Table 4. Test Products Results Summary

Fidelity Levels		**Predicted Time [s] (Percent Error)**		
ANN	**Test Assembly**	**Stapler**	**Flash Light**	**Ink Pen**
High	**High**	115.84 (-6%)	107.65 (43%)	54.78 (59%)
High	**Low**	119.43 (-3%)	91.79 (22%)	46.41 (35%)
Low	**High**	157.19 (27%)	109.89 (46%)	72.36 (110%)
Low	**Low**	198.30 (61%)	95.19 (26%)	51.65 (50%)
	Target Time [s]	123.51	75.40	34.40

The percent error from the target time was calculated for each of the outcomes (see **Fig. 3**, **Fig. 4**, and **Fig. 5**).

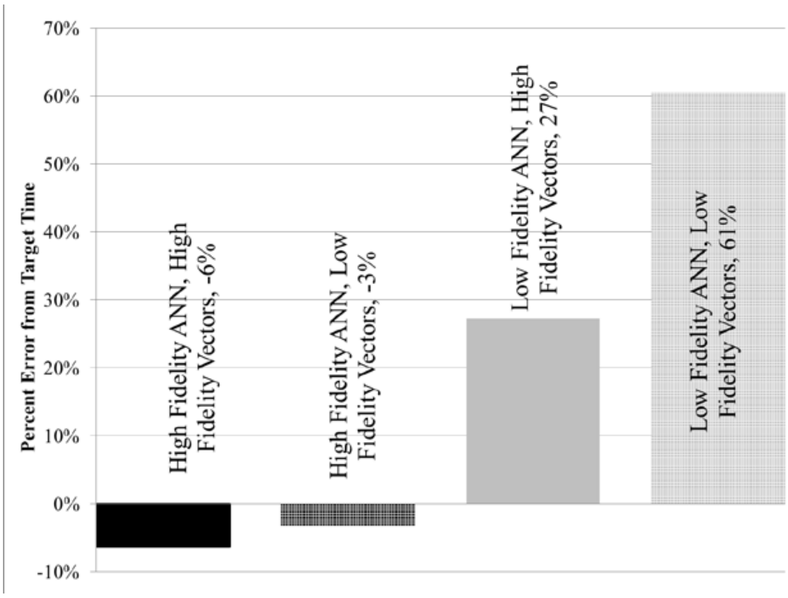


Fig. 3. Test Case Results for Stapler

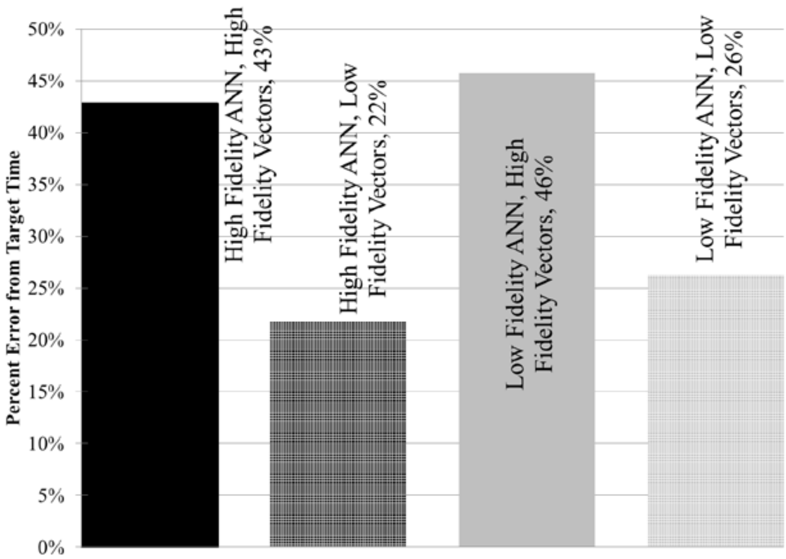


Fig. 4. Test Case Results for Flash Light

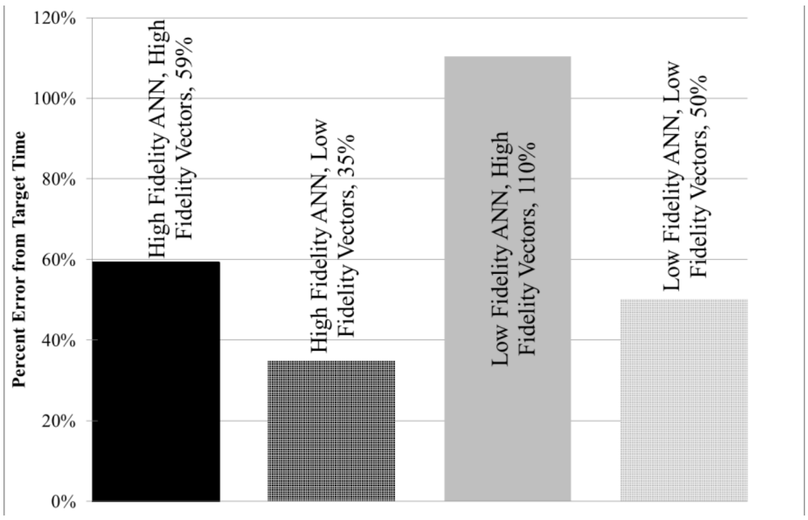


Fig. 5. Test Case Results for Ink Pen

The results from the analysis of the test cases indicate that both of the ANNs (high fidelity and low fidelity trained) can predict an assembly time to within 120% independent of the type of input vector used. However, the low fidelity ANN was the generally the worst at predicting assembly time when presented with a high fidelity input vector. The best combination of ANN and input vectors, based on the lowest percent error for all three test cases is the high fidelity ANN being provide low fidelity input vectors. The focus of this research is if an ANN can predict the assembly time of a low fidelity model. Both the high fidelity ANN and the low fidelity ANN were able to predict the assembly time of the conceptual model to within 120% of the target time. There was not sufficient evidence in this study to determine if there is a significant difference in assembly time estimation between the high fidelity and low fidelity ANN when using the low fidelity input vectors. The training sets and the test cases were limited in number and could potentially influence the results. The results of this study serve as motivation that there is potential to use an ANN to estimate the assembly time of models early in the design process.

4 Conclusions and Future Work

The ability of a neural network to create a relationship between input vectors and output vectors depends on the training set provided. The larger the training set (to a degree to avoid over fitting), the better the neural network is at predicting the output. While the input vectors used to train the neural network in this research are limited to ten training products, future work includes increasing the training set to determine if the assembly time estimation can be further improved. The number of test products will also be increased to ensure the trends in this limited population are valid. This paper presents the preliminary findings that must be extended with more validation.

The findings of this study suggest that the high fidelity assembly model based neural networks provide good prediction tools for estimating assembly time for both high fidelity and low fidelity conceptual models. There was not significant evidence to suggest that the high fidelity neural network or the low fidelity neural network can better predict assembly time. It is clear however that a neural network trained on low fidelity models should not be used to predict the assembly time of high fidelity models. Ultimately, this tool shows promise for providing engineers in conceptual stages of product development with useful information about production costs early in the design process. The accuracy of these predicted times are sufficient to provide justification for alternative engineering selection decisions at early stages.

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