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Accuracy and Precision Analysis of the Graph Complexity Connectivity Method

Sudarshan Sridhar[a], Mohammad Fazelpour[a], Amaninder S. Gill[a], Joshua D. Summers[a,]*

[a]*Department of Mechanical Engineering, Clemson University, Clemson, South Carolina 29634-0921, USA*

* Corresponding author. Tel.: +1-864-656-3295; fax: +1-864-656-4435. *E-mail address:* jsummer@clemson.edu

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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.

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

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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].

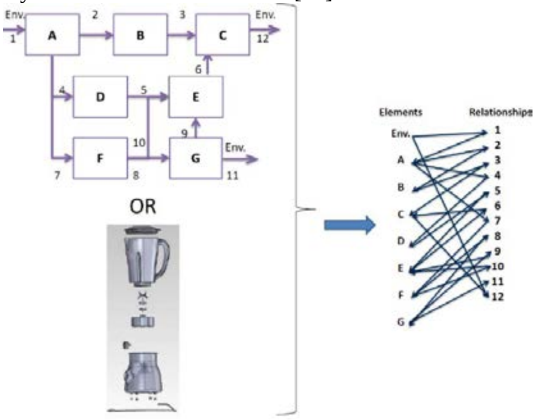

Fig. 1. Representation of a blender architecture as a bi-partite graph [14].

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