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SENSITIVITY AND PRECISION ANALYSIS OF THE GRAPH COMPLEXITY CONNECTIVITY METHOD

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ABSTRACT

In the Graph Complexity Connectivity Method (GCCM), twenty nine complexity metrics applied against engineering design graphs are used to create surrogate prediction models of engineering design representations (assembly models and function structures) for given product performance values (assembly time and market value). The performance of these prediction models has been previously assessed solely based on accuracy. In this thesis, 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 Assembly Model - Assembly Time (AM-AT) prediction model performed the best in terms of both accuracy and precision. This demonstrates that when given assembly models, one can consistently predict accurate assembly times.

Further, a sensitivity analysis is conducted to identify the significant complexity metrics in the estimation of the performance values, assembly time and market value. The results of the analysis suggest that for each prediction model, there exists at least one metric from each complexity class (size, interconnection, centrality, and decomposition) which is identified as a significant predictor. Two of the twenty nine complexity metrics are found to be significant for all four prediction models: number of elements and density of the in-core numbers. The significant complexity metrics were used to create simplified surrogate models to predict the product performance values. The test results indicate that the precision of the prediction models increases but the accuracy decreases when the unique significant metric sets are used. Finally, three experiments are conducted in order to investigate the effect of manipulation of the significant complexity metrics in predicting the performance values. The results suggest that the significant metric sets perform better in predicting the product performance values as compared to the manipulated metric sets of either union or intersection of metrics.

DEDICATION

I would like to dedicate this thesis to my beloved parents, Sridhar Ganesan and Mahalaxmi Sridhar, and to my sweet and loving sister, Aishwarya Sridhar. Their constant love and support gave me the required motivation, strength, and persistence to complete my thesis.

I would also like to convey my heartfelt thanks to my parents for believing in me and giving me this wonderful opportunity for higher education.

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Chapter One
COMPLEXITY IN ENGINEERING DESIGN: A REVIEW

One of the measures stressed in evaluating and comparing solutions in engineering design is simplicity [1–3]. This is often found under the general guide of “keep it simple”. Thus, conversely one might also consider complexity as a measure 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]. The question remains how can we use this measurement in making more informed decisions earlier in the design process? 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]. This is the reason why previous research has focused on measuring complexity in engineering design based on multiple metrics [7–20].

The existing complexity measurement methods refer to the term complexity with different interpretations [1,4,21,22]. In design for assembly, complexity is characterized by the number of assemblies and components involved [5,23], their connections [14,17,18] and the difficulties associated with their handling and insertion [2]. A design for manufacturing approach views complexity as a characteristic of part geometry and its implications on tooling construction costs [24]. Complexity measurement has continually been an active field of research in areas such as biology, computer science, and information theory [1,6]. Complexity in design is a measure of the information content of design problem, process and product [1,7]. In a broad sense, complexity can be defined as a quality of an object with many interwoven elements and details which makes the complete object difficult to understand in a collective view [25].

Designers predominantly define the complexity of a system based on the design problem and design process, while users define it depending on the design product [7]. Previous research has also explored the use of complexity as a surrogate for problem difficulty in predicting the effort or point value of an exam problem [26]. This is the reason for the existence of multiple definitions of the term complexity. The thesis deals particularly with measuring the structural complexity of electro-mechanical consumer products. In the context of this research, the following definitions would best describe the term complexity:

1. The amount of information required to describe a system comprised of more than one component [4,27].
2. 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 [17].

A review of the research that has been previously conducted in the field of engineering design complexity is presented in section 1.1. It encompasses the different views of complexity derived from graph theory, information theory, and design theory concluding with a comparison of these views forming the basis for design complexity measures.

1.1 Measuring complexity in design

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 section provides a brief overview of the different methods or approaches employed by researchers to measure complexity based on its contributing factors such as structure, amount of information, and connectivity. A tabular comparison of these methods based on multiple parameters has been included at the end of this chapter.

1.1.1 Structural complexity quantification

With an effort to objectify the process of system architecture design and selection, a quantitative structural complexity metric has been proposed by Sinha et al. [23]. This complexity metric encompasses the sum of complexities of individual components, number and complexity of each pairwise interaction, and topology. It is given by the following functional form:

$$C = C_1 + C_2 C_3 \tag{1}$$

where,

C_1 = sum of complexities of individual components

C_2 = number and complexity of each pairwise interaction

C_3 = topological complexity

The component complexity is assigned by experts on a [0, 5] scale. C_1 does not include any architectural information. The number and complexity of each pairwise interaction can be computed mathematically by using formula (2):

$$C_2 = \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} A_{ij} \tag{2}$$

where,

A_{ij} = adjacency matrix, which gives the number of interactions/connections between components

β_{ij} = interface complexity

Here, β_{ij} is assessed by experts on a scale of [0, 1] which makes it subject to variability. Topological complexity differentiates the structural complexities of two different connectivity structures which have the same number of components and interactions [23]. It can be measured with the help of the following equation:

$$C_3 = \Upsilon * E(A) = (1/n) * E(A) \tag{3}$$

where,

n = number of components in the system

E(A) = matrix energy of A, which is the sum of the absolute values of the Eigen values of the adjacency matrix A

Distribution of the overall complexity across the system's architecture is critical to achieving less complex subsystems; which will aid in large-scale system development efforts. This complexity quantification method was applied to two different jet engine architectures: a dual spool direct-drive turbofan (old architecture) and a geared turbofan engine (new architecture) [23,28]. The new architecture had a much higher development cost. Further, it was found that the geared turbofan engine had a 40% higher structural complexity as compared to the older one. This helped the researchers validate their hypothesis that structural complexity increase is a critical contributor to increase in system development costs. The research method provides valuable insights into structural complexity and its effect on system architecture with supporting evidence. However, there exists a certain degree of subjectivity in complexity measurement. The component and interface complexities were assigned by experts on a scale of [0, 5] and [0, 1] respectively. It is possible that different design experts assign distinct values of complexity to the same component or interface, which would ultimately result in a range of different values for the same entity's complexity. This warrants the need for further research to achieve objective measurements of complexity. This objectivity is critical to enable the application of complexity measures in design automation systems.

1.1.2 Ship design complexity

A metric for real-time assessment of complexity is critical to aid in the decision making process of ship designers in the design stage of a project [5]. The knowledge of the individual components solely is not sufficient to understand the ship's behavior. A complexity metric which would take into account shape, assembly, and material complexities would eventually help minimize production time and costs. The total ship design complexity can be expressed in the form:

$$C_T = (w_1C_{sh} + w_2C_{as} + w_3C_{mt})/(w_1+ w_2+ w_3) \quad (4)$$

where,

C_{sh} = shape complexity
C_{as} = assembly complexity
C_{mt} = material complexity

The shape complexity represents the degree to which a shape is compact. It is an important factor for determining the resolution of mesh generation in the field of Finite Element Modelling (FEM) [5,29]. Sphericity is commonly used for measuring the complexity of 3D shapes. It can be defined as the ratio of the lateral surface of a sphere to the surface area of a 3D solid. This ratio has a maximum value of 1 for spheres, and a minimum value of 0 for infinitely long and narrow shapes.

The average shape complexity of a set of parts can be computed using the equation:

$$\mathrm{Csh} = \sum_{i=1}^{n} [(1 - \psi n)\ /n] \quad (4)$$

where,

$\boldsymbol{\psi}$ = sphericity = $A_s/A = (\pi^{1/3}(6V)^{2/3)}) / A$
A_s = lateral surface of the sphere
A = lateral surface of the solid
V = volume of the solid

Assembly complexity signifies the extent of diversity amongst the elements (components), subassemblies, and their connectivity with the help of a hierarchical assembly structure.

$$\text{Cas} = \sum_{i=1}^{n} C(Ti + Nt)\log_2(2^{kt} - 1) \quad (4)$$

where,

$\sum_{i=1}^{n} C(Ti)$ = complexity of n non-isomorphic subtrees (subassemblies)
N_t = number of elements
K_t = number of non-isomorphic branches

Material complexity for an assembly is by the equation,

$$C_{mt} = C_{pt} + C_{st} \quad (5)$$

where,

C_{pt} = Material complexity for plates
C_{st} = Material complexity for stiffeners

The term C_{pt} depicts the number of different combinations between plate thickness and material type whereas C_{st} gives the number of different combinations between profile types and material type. Unlike other complexity measurement methods, this method attempts to measure the complexity associated with materials. However, extensive research needs to be conducted to further improve the effectiveness of this measure. It fails to address the number of plates and stiffeners, plate thickness, profile types, and materials independently. Moreover, each combination is given a similar value of 1 which results in multiple different combinations ending up with the same material complexity. For example, 5 aluminum plates of 10 mm and 10 steel plates of 5 mm are each assigned a complexity value of 1. Also, no consideration is given for the possibility of variable thickness plates.

This method provides a good basis to measure various aspects of design complexity exclusively for ship design. Major modifications in the vocabulary and evaluation of certain complexity metric input variables need to be made in order to extend this method to other engineering design domains. A limitation to this method is the need for a detailed design of the system to calculate complexity. For instance, dimensional details such as part volume and thickness must be known to calculate complexity using this method. This renders the method inapplicable in the early design stage.

1.1.3 Information complexity

Axiomatic design involves mapping of two domains to achieve the desired design task, namely, the functional domain and the physical domain. The functional domain includes a set of minimum functions called the functional requirements (FRs) required to meet the design objective. The physical domain involves the design parameters (DPs) required to satisfy the FRs. The probability of the FRs being satisfied depends on the selection of DPs. This measure of uncertainty in satisfying the system functional requirements is called complexity [1]. Information content is used as the basis to quantify complexity.

The probability of satisfying the functional requirement is given by:

$$P(dr^l \leq FR \leq dr^u) = \int_{drl}^{dru} ps\,(FR)d(FR) \tag{6}$$

where,

$ps\ (FR)$ = system probability density function (pdf)
dr^l = lower limit of design range
dr^u = upper limit of design range

Information content I is defined in terms of the probability of success in satisfying the functional requirement [1]. The greater the information content, the greater the complexity. It can be measured using equation (7):

$$I = -\log_2 P = -\log_2 \int_{drl}^{dru} ps\,(FR)d(FR) \tag{7}$$

For an entire system,

$$I = \sum I_i = \sum -\log_2 P \tag{8}$$

where, P_i is the probability of success for satisfying the i_{th} functional requirement FR_i

Complexity can be further divided into two components: 1) Time-independent, which can further be divided into real and imaginary complexity, and 2) Time-dependent, which can be classified into combinatorial and periodic complexity [1]. Real complexity represents the design embodiment's uncertainty in satisfying the desired functional requirements at all times. The designer cannot always meet the desired functional requirements because the design range and the system range are not always necessarily identical. The common range, as the name suggests, is the overlap between these two ranges.

Thus, real complexity can be defined to be equal to the information content as,

$$C_R = I = \sum_{i=1}^{n} log_2 (1/P_i) \quad (9)$$

where, P_i is the probability of success for satisfying the i_{th} functional requirement FR_i

Real complexity can be reduced by making sure that the design is either decoupled or uncoupled. Imaginary complexity accounts for the designer's inability to thoroughly understand the design mapping, and his inability to achieve the desired design solution. In such cases, he will most probably resort to trial and error methods which brings to the table greater uncertainty and hence, higher complexity.

$$C_I = \ln (1/P) = \ln (n!) \quad (10)$$

where P is the probability of finding the correct combination of n DPs to satisfy the entire FRs.

This view of complexity ignores the possible interconnectivity of the information and the difficulty involved in extracting information from a minimal design representation. It suggests complexity to be a relative measure, relating what the desired objective is against what is known and unknown. It makes an attempt to capture the influence of the designer's understanding and perception of the design through the aspect of imaginary complexity. However, a challenge would be measuring this imaginary complexity accurately when the design is decoupled or coupled. Using this method would require the ability to determine the probability of the functional requirements being satisfied. This calls for an intermediate or an experienced designer.

The inputs required to measure complexity using this method are independent of representation and hence it is extendable to other domains. The research approach suggests that complexity increases in direct proportion with information content. This can be used as the basis for conducting further research to understand the ‘value’ of the information associated with design representations in the measurement of complexity.

1.1.4 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 (3D CAD models) are given [11,13,17] and market cost, when function structures are given [8,19]. This requires a representation of the system’s architecture, which is developed by tracking the connections between the system’s constituent elements in a bi-partite graph shown in Figure 1.1.

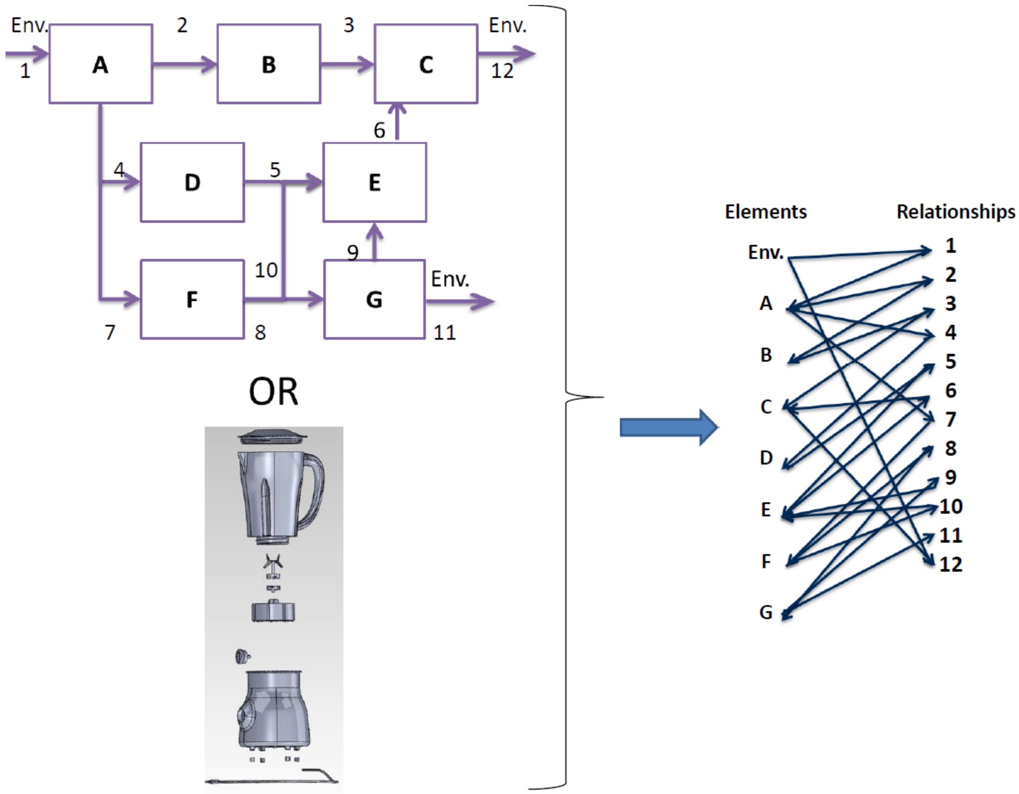


Figure 1.1: Representation of a blender architecture as a bi-partite graph

Graphs have been used from early stage requirements, function, and working principle models to latter stage geometric part and assembly models in engineering design [30–33]. 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 [23,34–37], 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 demonstrated in Table 1.1. These define the complexity vector used to create the surrogate prediction models.

Initially, the GCCM demonstrated the capability of complexity metrics to form a surrogate mapping between physical system architecture and assembly times based on the

Boothroyd and Dewhurst Design for Assembly (DFA) tables [17]. The method employed a power regression model (log-log regression) for predicting assembly times since it indicated the highest correlation of the other regression models evaluated. The regression model can be represented by the following equation:

$$t_a = [APL] \text{ X } n^{[1.185+PLD]} \qquad (11)$$

where,

t_a = assembly time,
APL = Average path length,
n = number of elements,
PLD = Path length density

Table 1.1: Complexity metrics

<table>
<tr><th rowspan="2">Class</th><th rowspan="2">Type</th><th rowspan="2">Direction</th><th>Metrics</th></tr>
<tr><th>Comp. vector</th></tr>
<tr><td rowspan="4">Size</td><td colspan="2" rowspan="2">Dimensional</td><td>Elements</td></tr>
<tr><td>Relationships</td></tr>
<tr><td colspan="2" rowspan="2">Connective</td><td>DOF</td></tr>
<tr><td>Connections</td></tr>
<tr><td rowspan="8">Interconnection</td><td colspan="2" rowspan="4">Shortest Path</td><td>Sum</td></tr>
<tr><td>Max</td></tr>
<tr><td>Mean</td></tr>
<tr><td>Density</td></tr>
<tr><td colspan="2" rowspan="4">Flow Rate</td><td>Sum</td></tr>
<tr><td>Max</td></tr>
<tr><td>Mean</td></tr>
<tr><td>Density</td></tr>
<tr><td rowspan="8">Centrality</td><td colspan="2" rowspan="4">Betweenness</td><td>Sum</td></tr>
<tr><td>Max</td></tr>
<tr><td>Mean</td></tr>
<tr><td>Density</td></tr>
<tr><td colspan="2" rowspan="4">Clustering Coefficient</td><td>Sum</td></tr>
<tr><td>Max</td></tr>
<tr><td>Mean</td></tr>
<tr><td>Density</td></tr>
<tr><td rowspan="9">Decomposition</td><td colspan="3">Ameri Summers</td></tr>
<tr><td rowspan="8">Core Numbers</td><td rowspan="4">In</td><td>Sum</td></tr>
<tr><td>Max</td></tr>
<tr><td>Mean</td></tr>
<tr><td>Density</td></tr>
<tr><td rowspan="4">Out</td><td>Sum</td></tr>
<tr><td>Max</td></tr>
<tr><td>Mean</td></tr>
<tr><td>Density</td></tr>
</table>

Total path length is the number of connections when all the information flow is considered. Total path length divided by the size of the path length matrix minus the empty identity gives the average path length. Average path length divided by the number of relationships in the system gives the Path Length Density. The model, applied against a training set of different electro-mechanical consumer products, estimated assembly times within a percentage error of ±16% with respect to the assembly times predicted by the Boothroyd and Dewhurst DFA tables.

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 [12]. 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. The analysis duration was found to be similar for both methods. It was determined that the Boothroyd and Dewhurst DFMA software required a larger amount of input information of forty nine questions per part, thirty three of which were objective. The GCCM required five questions per part, all of which are subjective. Although its accuracy could be further improved, this indicated that the GCCM can be automated as it solely requires objective information [12].

Initially, the GCCM manually created the bi-partite graphs and predicted assembly times using regression models. But due to the extensive effort required to create the bi-partite graphs, and to map the connective graph metrics to the product assembly time; automated graph generation and prediction methods were explored [9,11,16,20,38]. To make graph generation faster and accurate, the Assembly Mate Method (AMM) was incorporated which uses SolidWorks (SW) assembly mate information to create the connectivity graphs needed for the GCCM [9]. Mates create geometric relationships between assembly components which allow for defining the allowable directions of linear or rotational motion of the components. For example, a coincident mate makes two planar faces become coplanar whereas a concentric mate forces two cylindrical faces to turn concentric.

Continuing the previous work to predict assembly times from detailed assembly models, a series of predictive performance experiments were performed on low fidelity assembly CAD models [14]. 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. Each of the two ANNs was made to predict the assembly time of a test data set consisting of three products using the high-fidelity and low-fidelity models as seen in Table 1.2.

Table 1.2: Experimental design sets (Adapted from [14])

Set	ANN trained on	ANN tested on
1	High fidelity assembly models	High fidelity assembly models
2	High fidelity assembly models	Low fidelity assembly models
3	Low fidelity assembly models	High fidelity assembly models
4	Low fidelity assembly models	Low fidelity assembly models

It was observed that a neural network trained on low fidelity models did not fare well when used to predict the assembly time of high fidelity models. The best combination of ANN and input model fidelity level, based on the lowest percent error for all three test cases was found to be the high fidelity ANN with low fidelity input vectors. 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 CAD models [14]. 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 [14]. Ultimately, this research justified the use of low fidelity assembly CAD models for providing designers in conceptual stages of product development with a tool to evaluate and compare multiple early-stage design decisions.

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 [11,13,17] and market cost given function structures [19]. This method uses historical data in the form of product graphs transformed to a vector of twenty nine complexity metrics coupled with performance values to create artificial neural network based surrogate models. 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]. Table 1.3 illustrates the Absolute Average Percentage Error, also known as accuracy, of the five test products (Sander, Hair Dryer, Lawn Mower, Flashlight and Food Chopper) for the four prediction models.

Table 1.3: Comparative Study of the Absolute Average Percentage Error of the four prediction models in predicting Product Performance [16]

	Assembly Time (AT)	**Market Value (MV)**

Assembly Models (AM)	Average: 5% Maximum: 10% Previous Error 20% [15]	Average: 12% Maximum: 23% [8]
Function Structures (FS)	Average: 29% Maximum: 60% [8]	Average: 57% Maximum: 154% Previous Error: 50% [19]

The prediction results for the Assembly Models –Assembly Time and Function Structures – Market Value models were found to be in line with the previous research test results [15,19]. Between assembly models and function structures, use of assembly models as the input vector for the prediction model demonstrated a lesser absolute average percentage error in each of the four cases. The prediction model, 'Assembly Time estimation based on Assembly (CAD) Models', had the lowest absolute average percentage error of 5% when compared to accuracy of predicting within 20% of target time portrayed in [39] whereas the prediction model, 'Market Value estimation based on Function Structures' had the highest absolute average percentage error of 57% when compared to accuracy of predicting within 50% of target time displayed in [19].

In the order of lowest to highest absolute average percentage error, the four prediction models can be ranked as follows:

Table 1.4: Ranking of the four prediction models based on accuracy

Rank	Prediction model
I	Assembly Models - Assembly Time

II	Assembly Models - Market Value
III	Function Structures - Assembly Time
IV	Function Structures - Market Value

The approach to measuring complexity in the GCCM is objective and can be applied to different representations [26]. In their research, the factors and sources of problem difficulty are examined and compared to the structural complexity of a graphical representation of the problem solution. This research is an extended application of the GCCM.

1.2 Comparison of complexity methods

The complexity measurement methods discussed in this chapter (See sections 1.1.1 - 1.1.4) differ from each other based on certain parameters as shown in Table 1.5.

Table 1.5: Comparison of complexity measurement methods

Method	Reference	Basis	Metric	Information required	Dimension details	Representation
1	Sinha et al. 2013	SD	R	n, c, t	No	I
2	Caprace et al. 2012	SD	R	n, c, m, s	Yes	D
3	Suh 1999	ID	R	FRs, DPs	No	I
4	Mathieson et al. 2012	SD	A	n, c, t	No	I

Legend:

n = number of components	c = number of connections
t = topology	m = material
s = shape	FRs = functional requirements
DPs = design parameters	SD = Structural Design
ID = Information content in Design	I = Independent
D = Dependent	R = Relative
A = Absolute	

The top two and the bottommost methods in Table 1.5 use structural design as the basis to evaluate and measure complexity whereas method 3 views complexity as a measure of the information content contained within a design representation. The top three complexity methods provide relative measures of complexity. Method 3 measures complexity by relating the current information content with the amount of information required to satisfy the design problem [1,4] while methods 1 and 2 require certain input parameters that are assigned by expert designers, thus rendering complexity to be a relative measure. However, method 4 proposes complexity metrics that are objective in that they are dependent on a model generated to represent the design product and independent of a designer’s interpretation of information [4]. The common parameter considered in all the methods is size, which is represented by the number of components in methods 1, 2, and 4 and by the amount of information in method 3. Method 2 requires the most amount of information (four input variables) as compared to the others. Out of the four, only method 2 requires the dimensional details of the system to be able to calculate complexity. The complexity measurement methods 1, 3, and 4 are independent of the form of representation. As the design transitions amongst different forms of representations, the information contained within the characterization of the product changes. Method 2 on the other hand is dependent on a single form of representation, that being of ship design.

Each of the top three methods mentioned in Table 1.5 are either relative complexity measures or dependent on the form of representation. However method 4, the GCCM, is independent of a representation model and involves the use of objective structural complexity metrics. Objectivity is a key factor in enabling comparison and evaluation of multiple design solutions based on their complexities. This method inputs twenty nine complexity metrics as a vector into artificial neural networks (ANNs) which generate 18900 estimates of the required output performance value. The large number of sample points involved in prediction and the objectivity of this method provide motivation to conduct further studies on the GCCM. This thesis will focus mainly on evaluating the variability of the 18900 estimates (precision) and the sensitivity (significance) of the twenty nine complexity metrics.

Chapter Two
MOTIVATION AND RESEARCH QUESTIONS

The architecture of engineered systems is becoming progressively complex due to increased functional performance requirements and cost demands [23,40]. These architectures consist of a set of interrelated components which, through their interconnectivity, manifest a behavior which the individual components would not display independently [41]. This calls for a robust method that can attempt to quantify our understanding of these components and interrelations which are counterintuitive [40], and use these measurements to make informed decisions. However, such measurements are inherently limited in their applicability and not always clear in their implications [18]. The higher structural complexity of a design increases the system cost and makes it more susceptible to failure [9]. Designers must consider complexity when design decisions are made in order to achieve the optimum system architecture with the desired complexity.

The GCCM is used as the backbone of this thesis. This is because the complexity metrics evaluated using this method are objective in that they are independent of a designer's interpretation of information [4]. To date, the research efforts in this method have been focused on the development of surrogate prediction models [4,8,9,11–17,19,20,38,39,42]. These prediction models use engineering design representations (assembly models and function structures) to predict product performance values (assembly time and market value). The performance of these prediction models has been previously assessed solely based on accuracy. In this thesis, 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. 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.

This thesis will also focus on understanding complexity as an enabler in prediction. This will be accomplished by identifying the complexity metrics that are influential (significant) in predicting the product performance values for each of the four surrogate prediction models. An outline of the GCCM is provided in Figure 2.1. This will help illustrate the method flow step by step (marked in blue) and identify the research questions (marked in red).

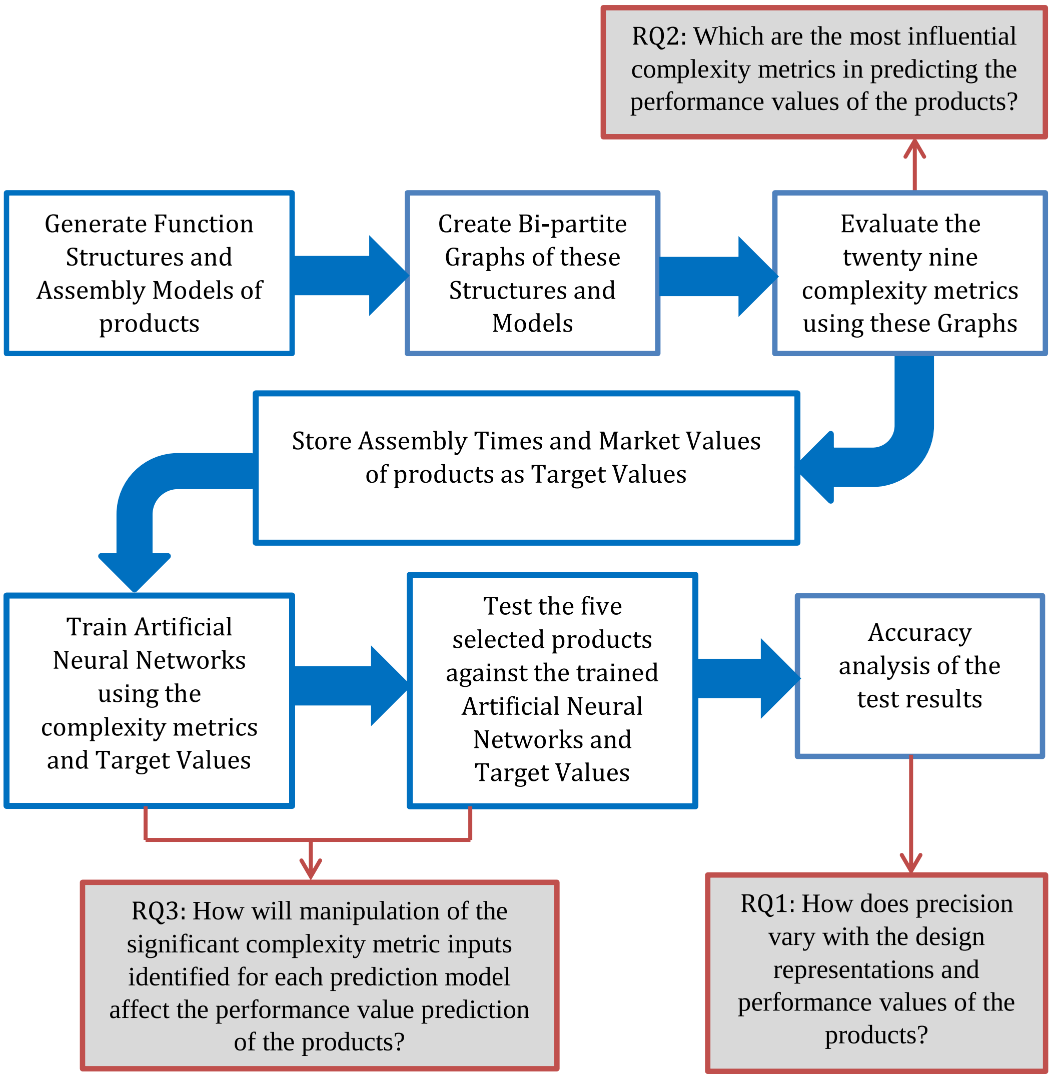


Figure 2.1 Outline of the GCCM with the identified research questions

2.1 Research Questions

The following three research questions are presented to address the research gaps identified from the Graph Complexity Connectivity Method (GCCM).

Research Question 1: *How does precision vary with the design representations (assembly models and function structures) and performance values of the products (assembly time and market value)?*

Hypothesis 1: *The performance ranking order of the four prediction models with respect to predictive precision will be similar to their ranking order based on predictive accuracy.*

The GCCM has shown the potential to create surrogate prediction models of assembly times and market values at the early design stage, given either product assembly models [11,13,17] or function structures [8,19]. The four prediction models have been evaluated and compared solely based on the accuracy of their prediction in previous research [8]. Answering research question 1 motivates the need for a precision analysis to understand the closeness of agreement between the estimates and their deviation from the mean value.

Research Question 2: *Which are the most influential complexity metrics in predicting the performance values of the products?*

Hypothesis 2.1: *There are some complexity metrics that will be significant across all the four prediction models.*

Hypothesis 2.2: *The classes of complexity metrics will not have the same significance as each other.*

The GCCM makes use of twenty nine complexity metrics divided across four classes as the input to train the artificial neural network (ANN). These metrics were developed and integrated into the method over time in an effort to capture all the aspects of system complexity and improve the performance value prediction [4,43]. A statistical study was conducted to determine the significant complexity metrics for product assembly models to predict assembly times [15]. However, we need to understand the contribution of each metric in predicting the performance values across all the four prediction models, namely, Assembly Model – Assembly Time, Assembly Model – Market Value, Function Structure – Assembly Time, and Function Structure - Market Value.

This second research question will be addressed by executing a multiple linear regression analysis of the twenty nine complexity metrics with the 18900 ANN training estimates as the responses. Further, a comparative study of the performance value prediction models using both the original set of twenty nine metrics and the new sets of significant metrics will be performed.

> ***Research Question 3:*** *How will manipulation of the significant complexity metric inputs identified for each prediction model affect the performance value prediction of the products?*

In order to address research question 3, all the identified significant complexity metrics for the four prediction models would be divided into two different sets and then the prediction accuracy and precision would be examined. One set will contain the common significant metrics across the four models and the other set would contain the union of the significant metrics across the four models. Answering research question 3 will help evaluate the sensitivity of changes in the predicted performance values.

2.2 Thesis outline

In this thesis, the research questions are defined and addressed through six chapters as shown in Figure 2.2.

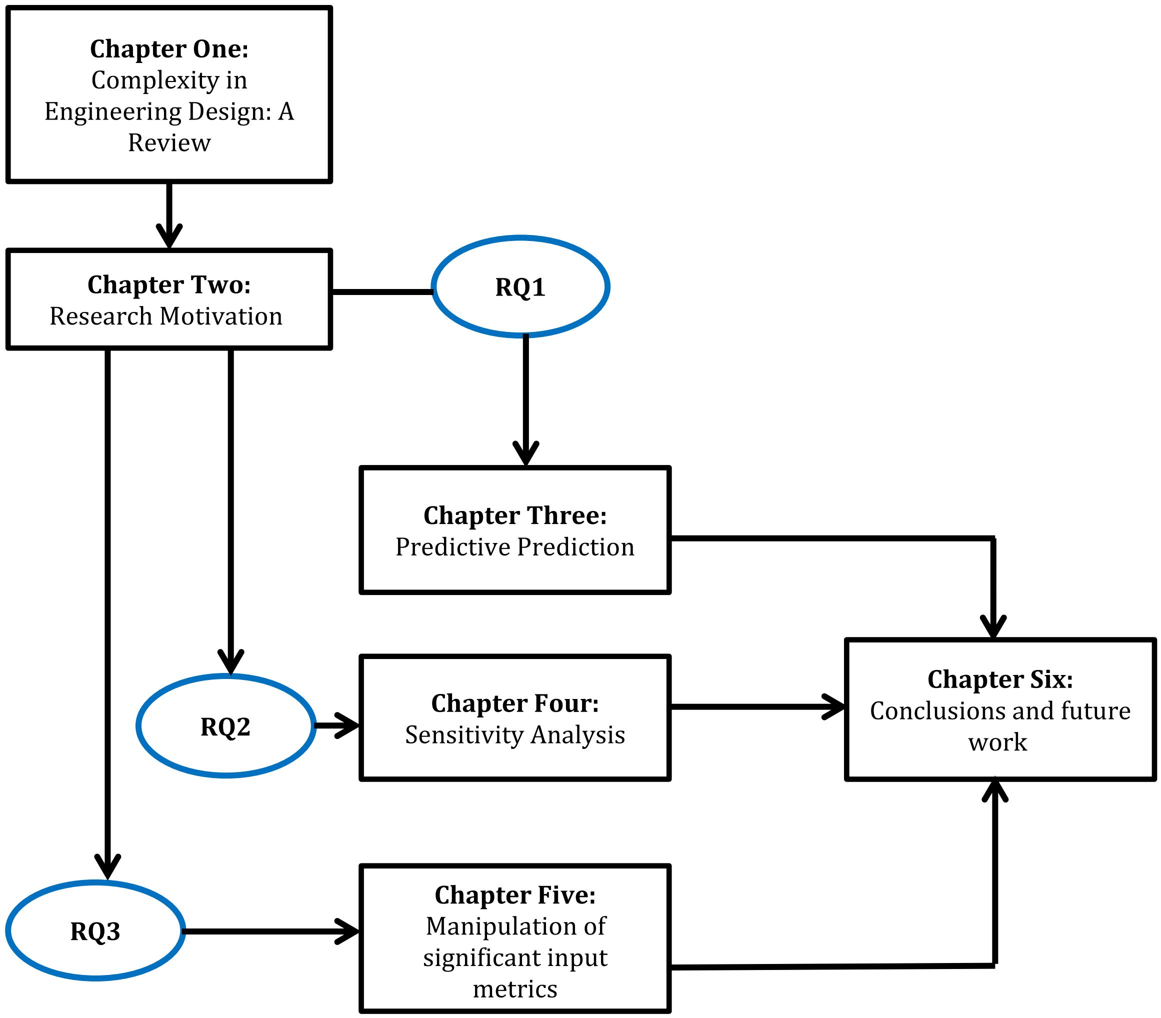


Figure 2.2: Outline of the thesis

The literature review conducted in the area of engineering design complexity in chapter 1 facilitates in identifying the research gaps which ultimately form the basis of the thesis research questions.

Chapter Two helps establish the motivation behind the purpose of the thesis. It begins with a brief outline of the GCCM which would form the backbone of this thesis.

Three research questions are then presented to address the research gaps identified from the GCCM. The chapter concludes with an outline of the thesis.

The experimental method employed for predicting the performance values is explained in Chapter Three. The chapter also addresses the first research question through the precision analysis of the design representations (assembly models and function structures) in predicting the performance values of the products (assembly time and market value). The results of the precision analysis are further compared to the accuracy analysis results previously evaluated [8] for all the four prediction models.

Chapter Four concerns the examination of the twenty nine complexity metrics to determine the influence of each metric in predicting the performance values: assembly time and market value. The second research question is addressed in this chapter by identifying the significant complexity metrics for each of the four prediction models.

In Chapter Five, all the significant complexity metrics from the four prediction models are divided into two different sets which are then used to train and test the ANN. The ANN test estimates are further examined for predictive accuracy and precision to address the third research question.

The conclusions of the analyses conducted in Chapter Three through Chapter Five are summarized in Chapter Six along with recommendations for future work.

Chapter Three
ASSESSMENT OF PREDICTIVE PRECISION

Previous research focused on validating the effectiveness of the surrogate prediction models of assembly time and market cost, when product assembly models and function structures are given [8,16,17,19]. Accuracy of prediction was used as the sole measure of effectiveness to compare and rank the four prediction models [8,16]. Accuracy gives the closeness of the absolute average of the 18,900 estimated values to the target performance value. Nonetheless, it is imperative to note that it is not possible to reliably attain accuracy without precision [44]. This chapter seeks to examine the precision of the design representations (assembly models and function structures) in predicting the performance values of the products (assembly time and market value). The measure of precision (also repeatability) represents a method's ability to show consistent results under the same conditions [45,46]. It will enable one to characterize how close the 18,900 estimated values are to each other and indicate the range of values (standard deviation) within which the true value is asserted to lie with some level of confidence. A large standard deviation relative to the estimate indicates low precision and a small standard deviation relative to the estimate indicates high precision.

In this thesis, 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. 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. Section 3.1 illustrates the procedure followed to conduct the precision analysis for the four surrogate prediction models which are exhibited in Table 3.1.

Table 3.1: Design representation based surrogate prediction models

	Design Representation	**Performance value**
1	Assembly Models	Assembly Time
2	Assembly Models	Market Value
3	Function Structures	Assembly Time
4	Function Structures	Market Value

3.1 Experimental method for prediction

The GCCM was employed as the experimental method for predicting the performance values: assembly time and market value. A flowchart of the experimental method is illustrated in Figure 3.1. The method is systematically explained in sections 3.1.1 through 3.1.5.

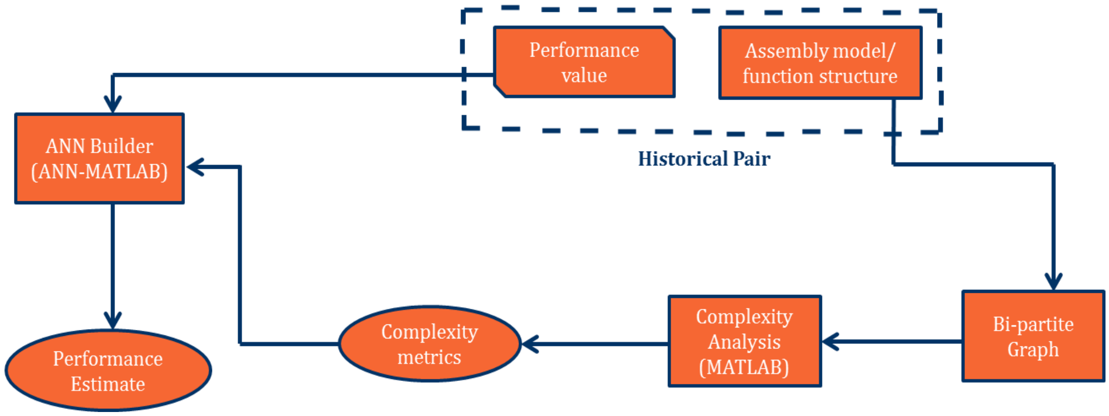


Figure 3.1: Flow chart of the prediction experimental method

3.1.1 Dataset

The experimental method utilized a data set of twenty electro-mechanical consumer products for performance value prediction. Fifteen out of these twenty products were applied for training the Artificial Neural Networks (ANNs) and the remaining five were tested using the trained ANN. A brief description about the ANNs and their architecture is provided in Section 3.1.5. The products were first characterized into two different design representations, function structures and assembly models. This provides a diversity in product design representation in that the assembly models represent a product's form dependent blueprint whereas the function structures constitute a product's form independent blueprint [47]. Thus the method is not dependent on an engineer's interpretation of product design, but rather on the design representation. This helps in developing objective measures of complexity.

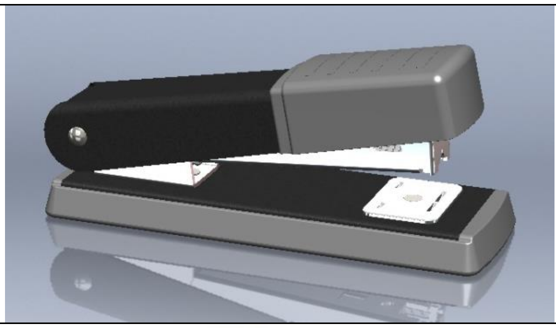
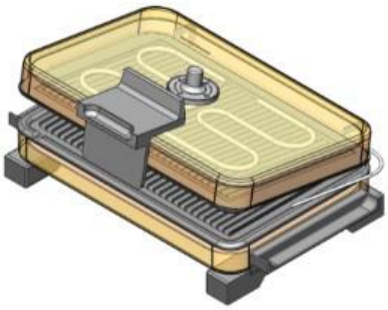
3.1.1.1 Assembly Models

In industries, assembly modeling is done with the help of computer-aided design and product visualization software systems. An assembly model represents multiple parts that are joined together to perform a specific function [48]. The parts within an assembly are represented as solid or surface models. Assembly models essentially facilitate the evaluation of a product's structural aspects such as size (number of components), connectivity (mates between subcomponents), centrality (how central is each subcomponent) and decomposition (ease of disassembly). This characteristic of assembly models is utilized in this method to objectively extract the product's complexity [8,9,11,15–17,20,38]

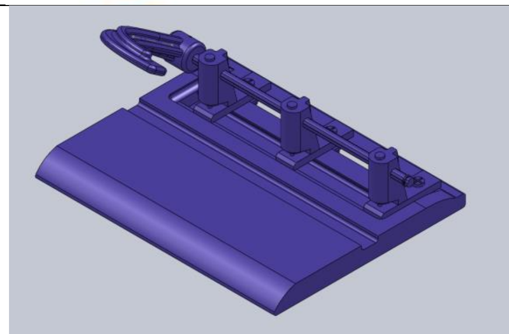
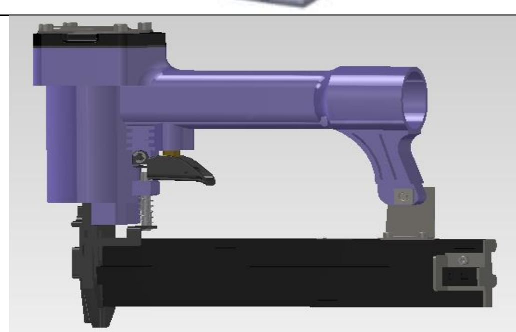
The assembly models of the twenty products used in the prediction of assembly time and market value were obtained from three different sources. Most of the models were used in previous research [9] and were created by different engineering design graduate students, but not the author of this thesis, by reverse engineering existing products. One of the product assembly models was obtained from a local original equipment manufacturer (OEM). The name of the local OEM is not disclosed due to proprietary reasons. The assembly models of the remaining products were obtained from the online CAD libraries, *GrabCAD*[1] and *3D CONTENT CENTRAL*[2]. These products were divided randomly into two sets for ANN training and testing purposes. The training set consisting of fifteen products is depicted in Table 3.2 and the test set is illustrated in Table 3.3.

[1] **https://grabcad.com/** (last accessed 2015.06.10)
[2] **http://www.3dcontentcentral.com/default.aspx** (last accessed 2015.06.10)

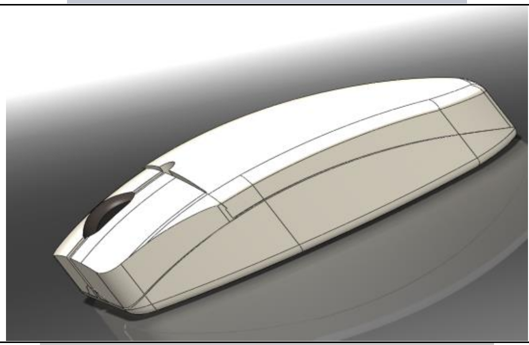
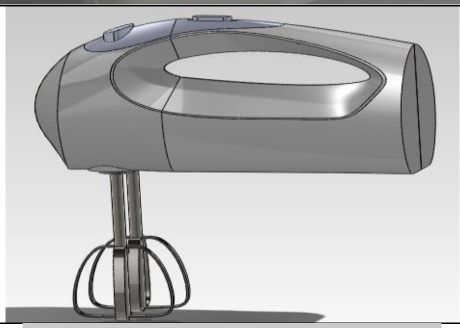
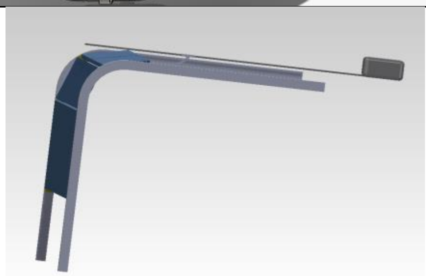
Table 3.2: ANN Training products set

	Training products set	CAD Model Image	Source
1	Stapler		*GrabCAD*[3]
2	Electric Grill		Reverse Engineered [9]
3	Juice extractor		*GrabCAD*[4]
4	Solar Yard Light		Reverse Engineered [9]

[3] **https://grabcad.com/**
[4] **https://grabcad.com/**

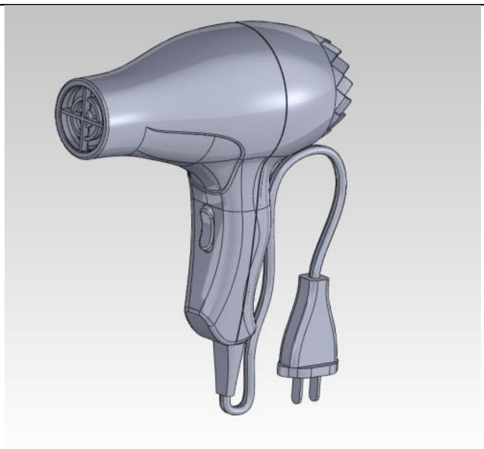
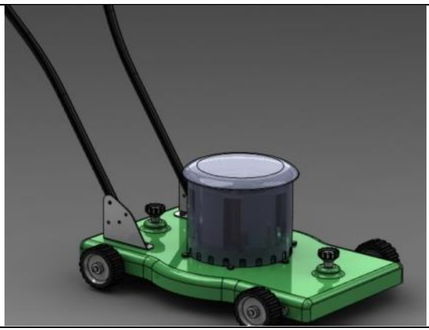
	Training products set	CAD Model Image	Source
5	Bench Vise		Reverse Engineered [9]
6	3 Hole Punch		Reverse Engineered [9]
7	Electric Drill		Reverse Engineered [9]
8	Nail gun		*GrabCAD*[5]

[5] https://grabcad.com/

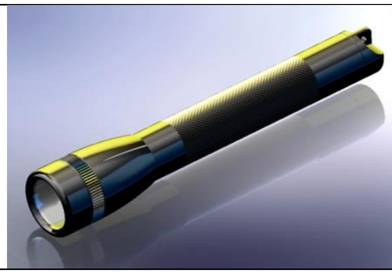
	Training products set	CAD Model Image	Source
9	Blender		Reverse Engineered [8]
10	Computer Mouse		Reverse Engineered [9]
11	Food Mixer		Reverse Engineered [9]
12	Garage door opener		Reverse Engineered [8]

	Training products set	CAD Model Image	Source
13	Jigsaw		OEM [15]
14	Electric toothbrush		Reverse Engineered [8]
15	Sewing Machine		Reverse Engineered [8]

Table 3.3: ANN Test products set

	Test product set	CAD Model Image	Source
1	Sander		*3D CONTENT CENTRAL*[6]
2	Hair dryer		Reverse Engineered [8]
3	Lawn mower		*GrabCAD*[7]

[6] http://www.3dcontentcentral.com/default.aspx
[7] https://grabcad.com/

	Test product set	CAD Model Image	Source
4	Flashlight		*GrabCAD*[8]
5	Food chopper		Reverse Engineered [9]

3.1.1.2 Function Structures

Function structures are utilized during the conceptual stage of engineering design in order to interpret the customer requirements in the shape of specific functional tasks [49]. Function Structures are selected as one of the design representations in this method because it allows designers to break down a product's overall function into simpler subfunctions while showing their connectivity in terms of flows. A function structure is a graphical illustration of a functional model, wherein the overall function is represented by a number of subfunctions connected by the flows on which they operate. A function can be defined as a description of an operation to be performed by a device which is expressed as the action verb of a function block [47,49]. A flow is defined as a change in

[8] **https://grabcad.com/**

energy, material or signal with time, expressed as the object of a function block [47]. The function structure of one of the products used for the analysis, namely, a food mixer is shown in Figure 3.2. The function structures of the other products are listed in the appendix section of the thesis for brevity.

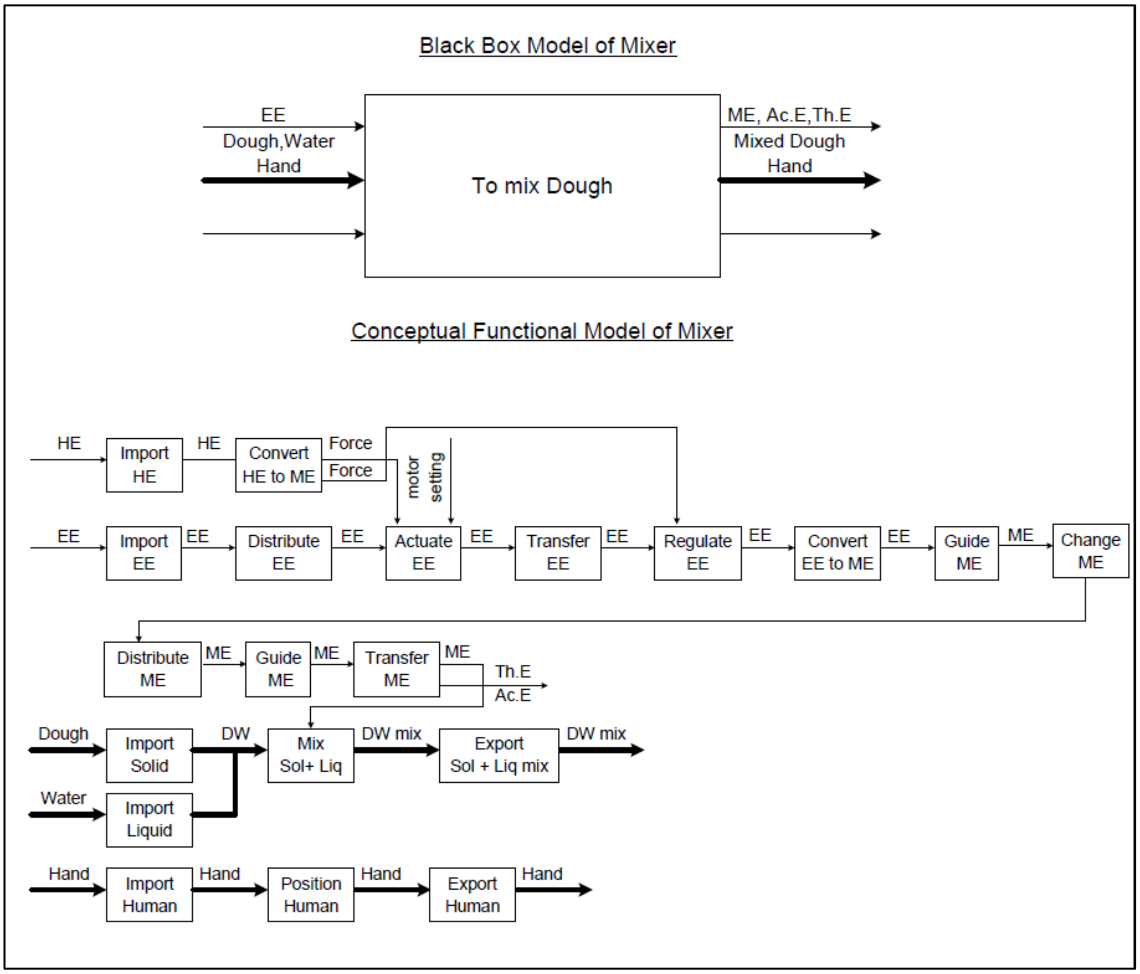


Figure 3.2: Function Structure of a Food Mixer (Source: Oregon State Design Repository[9])

[9] http://function2.mime.oregonstate.edu:8080/view/index.jsp

Some of the function structures were created manually by mechanical engineering graduate students, but not the author of this thesis, while the others were obtained from the *Oregon State Design Repository*[10]. The repository is the result of collaborative efforts of researchers from Oregon State University, the University of Texas at Austin, Missouri University of Science and Technology, and NIST.

3.1.2 Bi-partite Graphs

Graphs have been used extensively in engineering design right from early stage requirements, functions, and working prototypes to latter stage part and assembly models [30–33]. They help portray information in a simple and concise, yet effective manner. Graph-based representations such as bond graphs [50], bi-partite graphs [51,52], design exemplars [51,53], parametric-constraint graphs [4,52], or semantic networks [54] are generally used for representing product architectures. In this method the function structures and assembly models of the twenty products were further transformed into bi-partite graphs, with nodes and edges depicting the entities and relationships respectively [51,52]. Bi-partite graphs consist of two independent sets. In case of assembly models the first independent set (left-hand side) comprises of the product's physical parts, including both major system components and fasteners. The second independent set (right-hand side) depicts the relationships, namely, instances of contact between these parts (see Figure 3.3).

[10] **http://function2.mime.oregonstate.edu:8080/view/index.jsp**

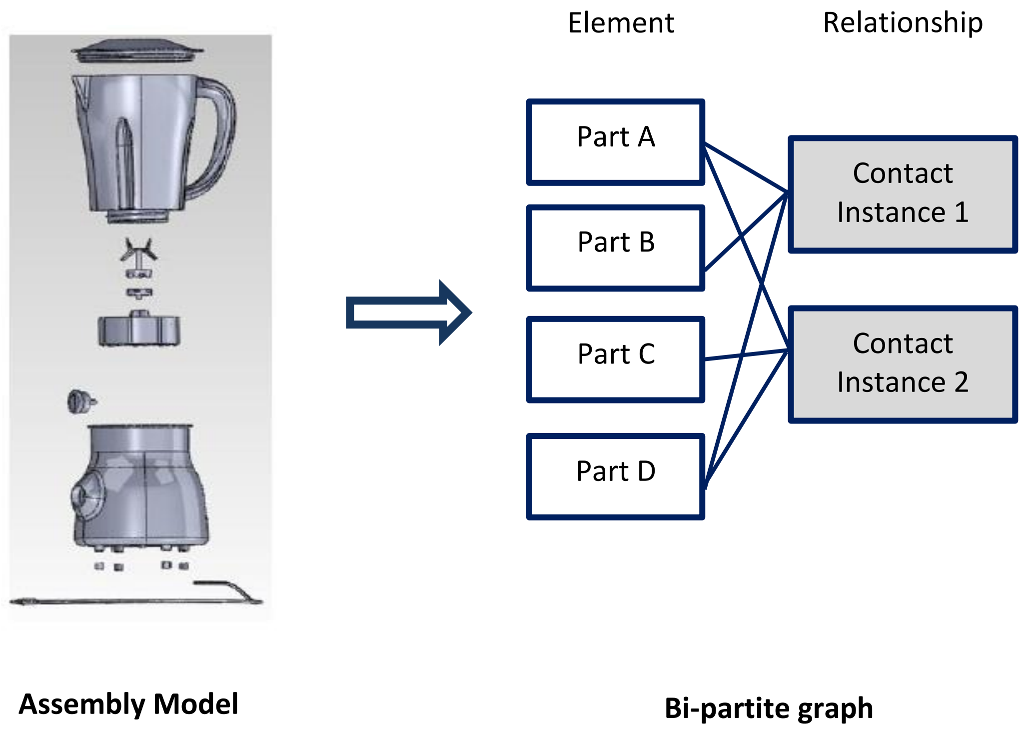
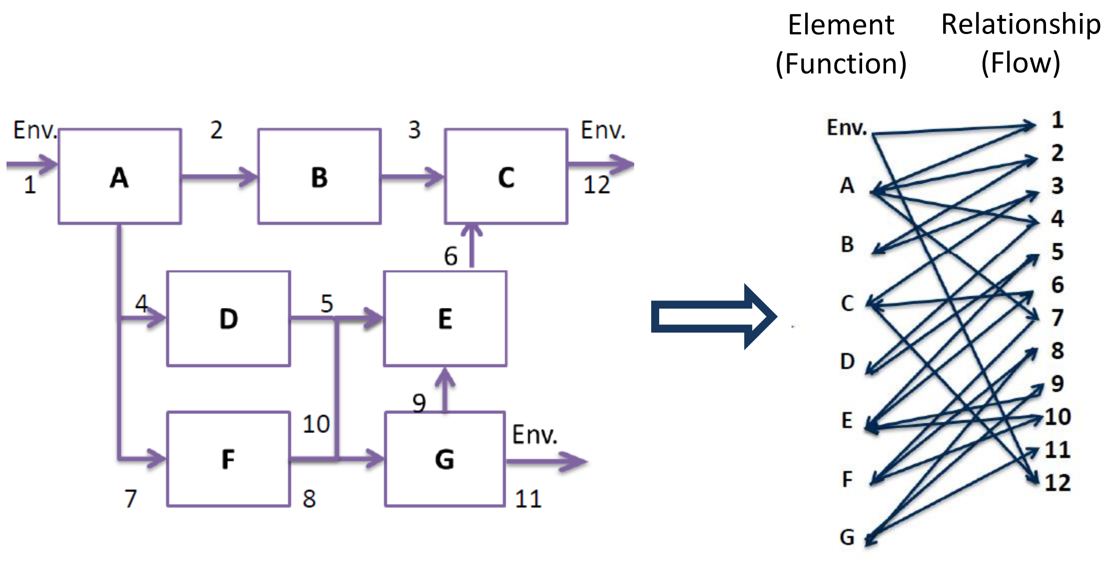


Figure 3.3: Translation of Assembly Model into bi-partite graph

Figure 3.4 depicts the bi-partite graph corresponding to a function structure. In this graph, the left-hand-side nodes represent the elements in the function structure (functions) and the right-hand-side nodes denote the relationships which exist between the identified entities (flows).



Function Structure **Bi-partite graph**

Figure 3.4: Translation of Function Structure into bi-partite graph

The bi-partite graphs corresponding to the twenty product assembly models and function structures were evaluated against the structural complexity metrics to form a complexity vector describing each product.

3.1.3 Metrics of structural complexity

Twenty nine structural complexity metrics were evaluated for each of the twenty electro-mechanical consumer products. Fifteen out of these twenty products were used for training the ANNs and the remaining five were used to test the ANNs. These metrics are a combination of several distinct properties contributing to product complexity: size, interconnectivity, centrality, and decomposition. The complete set of complexity metrics are depicted in Table 3.4. These define the complexity vector used to create the surrogate prediction models.

Table 3.4: Metrics of structural complexity

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

For brevity, a brief description of these structural complexity metrics is provided in Sections 3.1.3.1 through 3.1.3.4. The complete set of associated algorithms can be found in [18,55].

3.1.3.1 Size

In information theory, size is characterized by the information content in a system [1] whereas in structural design it represents the number of elements and possible relationships between these elements [4,17]. Size is a standard measurement parameter used in evaluating engineering design complexity. It is essentially based on the count of certain characteristics within the system [7,56]. Although it does follow plausibly that if the element count or information content in a system increases, so does the system complexity; some note that their influence on capturing complexity is non-linear [57]. Generally, when the product size is small, the addition of one more element is significant; however a similar addition in a large size product might not have the same influence on the product complexity. The class size covers both the dimensional and connective aspects.

Dimensional size concerns the evaluation of product elements and their relationships through a relational Design Structure Matrix (rDSM). The rDSM is an array-based hypergraph representation which recognizes pairs of elements that are affiliated via multiple relationship instances as also the relationships between multiple elements through a single instance [58]. A detailed explanation of the translation of bi-partite graphs into rDSM is provided by Mathieson et al. [18].

Connective size represents the quantity of arcs contained within the bipartite graph. It measures the connections between the elements and the degree of freedom, which is the parameter count that might vary in the system.

3.1.3.2 Interconnectivity

The size of the product alone is insufficient in capturing the product architecture [4,7]. It does help in evaluating the number of connections between the product elements but it does not indicate how these elements are connected to each other. Two products might have the same number of connections but the nature of these connections can be different which will in turn result in different product complexities. For instance, consider a bag full of building bricks and a building constructed using the same bricks. Although both have the same number of elements and connections, the building is evidently more complex with respect to the interconnectivity between the elements.

The measure interconnectivity examines the different possible combinations of relationships between the elements of a product. Interconnectivity is further broken down into two characteristics: shortest path and flow rate. The shortest path length measurements indicate the number of relationships that must be passed by to travel from one product element to another [58,59]. For instance, in Figure 3.5, housing 1 is connected to housing 2 through two contact instances. Thus the shortest path length in this case would be two.

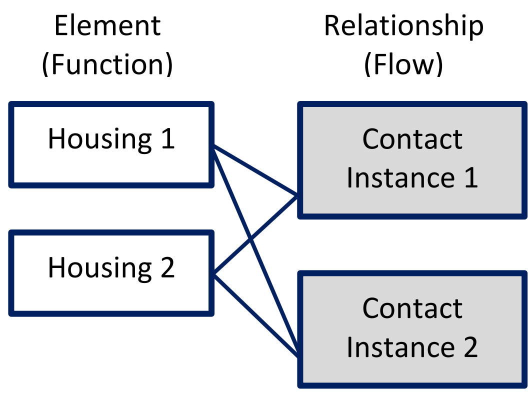


Figure 3.5: Shortest path length

Flow capacity evaluates the number of unique paths between each element pair in the product. The push-relabel maximum flow algorithm was applied to the degree of freedom multiple graphs projection to compute the flow capacity values [18,60].

3.1.3.3 Centrality

The measure of centrality extracts the relative importance of the different elements within a system. The two centrality measures that were evaluated for each element include betweenness centrality and the clustering coefficient. Betweenness, as the name suggests, depicts how central an element is to the other elements within a product structure. Betweenness centrality computes the number of shortest paths of which an element is a part of [61]; and the clustering coefficient gives a measure of the degree to which the elements are bunched within the product [62].

3.1.3.4 Decomposability

Decomposability measures the difficulty of disassembling a system one element at a time. The purpose is to identify and analyze the necessary actions for structural disassembly of a product. The Ameri-Summers decomposability algorithm [4] was developed to calculate this metric. The algorithm iteratively reduces the elements of the product with each iteration involving the elimination of relationships that contain the least number of connections with the elements. Essentially the product decomposability complexity increases in proportion with the number of iterations.

In decomposition, core numbers can be defined as the largest integer such that the given element exists in a graph where all degrees are at least that integer [63]. These degrees were separated into measurements relating to the in-degree and out-degree of each element node in digraphs.

The algorithms of all the twenty nine complexity metrics were computed using the programming language MATLAB; comprising of a combination of self-developed functions and the MatlabBGL implementation of the Boost Graph Library. The MATLAB code "EZ_ANN" transforms the bi-partite graphs into the twenty nine complexity metrics vector. The MATLAB codes can be found in the Appendix section of the thesis.

3.1.4 Product Performance Values

The product performance values evaluated in the experimental method include assembly time and market value (price). The assembly times and market values of the entire set of twenty products are illustrated in Tables 3.5 and 3.6.

3.1.4.1 Assembly Time

The assembly times of the products were evaluated manually based on the Boothroyd and Dewhurst tables for Design for Assembly (DFA) [19]. The Boothroyd and Dewhurst DFA method calculates assembly time as an aggregation of part handling and insertion times. Handling time is measured in terms of the level of difficulty experienced in grasping and maneuvering the assembly parts (elements). Insertion time is calculated as the time needed to place each part in the assembly. These product assembly times were further used as target values of the products for the two design representations: function structures and assembly models. These target values were later used as the performance output values to train ANNs. Table 3.5 illustrates the assembly times (in seconds) of the entire set of twenty products. The rows containing the five test product quotes are highlighted in this table in order to distinguish them from the products used for ANN training.

Table 3.5 : Product Assembly Times in seconds based on B&D DFA tables [8]

	Product Name	Assembly Time (Seconds)
1	Stapler	123.51
2	Electric Grill	121.08
3	Juice Extractor	76.65
4	Solar Yard Light	128.79
5	Bench Vise	143.69
6	3-Hole Punch	145.38
7	Electric Drill	189.65
8	Nail gun	90.44
9	Blender	263.21
10	Computer Mouse	81.25
11	Food Mixer	76.65
12	Garage Door Opener	196.50
13	Jigsaw	339.38
14	Electric tooth Brush	395.82
15	Sewing Machine	273.71
16	Sander	218.18
17	Hair Dryer	89.53
18	Lawn Mower	296.61
19	Flashlight	75.40
20	Food Chopper	316.62

3.1.4.2 Market Value (Price)

Five market value quotes in United States dollar ($) currency were procured from the Amazon Website[11] for each of the twenty consumer products. This was done to cover a range of values for each product corresponding to other equivalent products. The average value of these five market value quotes was calculated to obtain the target values for each product for the two design representations: function structures and assembly

[11] **http://www.amazon.com/**

models. These target values were later used as the performance output values to train ANNs.

The product quotes obtained from the Amazon Website[12] are illustrated in Table 3.6. The rows containing the five test product quotes are highlighted in this table in order to distinguish them from the products used for ANN training.

[12] **http://www.amazon.com/**

Table 3.6 : Product Market value quotes in $ [8] (Source: Amazon Website[13])

	Product Name	Quote 1($)	Quote 2($)	Quote 3($)	Quote 4($)	Quote 5($)	MEAN ($)
1	Stapler	24.88	17.67	14.69	16.13	16.83	18.04
2	Electric Grill	47.02	49.91	58.94	79.95	89.99	65.162
3	Juice Extractor	26.99	29.95	30.19	32.78	40	31.982
4	Solar Yard Light	1.663	1.937	2.997	3.75	4.123	2.894
5	Bench Vise	38.38	39.15	40.71	40.72	43.37	40.466
6	3 Hole Punch	57.91	62.99	63.83	71.56	73.5	65.958
7	Electric Drill	42.99	48.42	49.97	59.26	69.46	54.02
8	Nail gun	69	76.96	79.99	82.99	89.68	79.724
9	Blender	14.96	19.99	21.99	24.85	25.31	21.42
10	Computer Mouse	6.95	8.17	8.99	9	12.01	9.024
11	Food Mixer	8.99	9.89	13.22	14.96	19.99	13.41
12	Garage Door Opener	103.99	119.88	128	139	148	127.774
13	Jigsaw	114.99	117.5	78.99	74.999	139.95	105.286
14	Electric tooth Brush	79.99	95.99	96.9	119	129.95	104.366
15	Sewing Machine	75	125	175	129	69.99	114.798
16	Sander	169.95	189.9	204.97	214.95	295	214.954
17	Hair Dryer	14.99	20.96	23.99	24.49	26.95	22.276
18	Lawn Mower	99.99	114.99	135.99	137.97	143.99	126.586
19	Flashlight	17.89	17.76	20.38	20.65	24.92	20.32
20	Food Chopper	39.95	42.99	49	49	59	47.988

3.1.5 Artificial Neural Networks (ANNs)

Once the product complexity metrics were evaluated, the forecasting ability of Artificial Neural Networks (ANN) was utilized to map the relationships between them and the product performance values: assembly time and market value. ANNs were chosen for mapping the relationships on account of their ability to perform nonlinear statistical modeling [65]. Other machine learning approaches like the support vector

[13] **http://www.amazon.com/**

machines and decision trees were not considered to create prediction models as they do not provide a continuous differentiable output [20].

The ANN used for this method is a monitored back propagation network with a single hidden layer as recommended in previous research [9,20,66–68]. First, the ANNs were trained by providing the complexity vector as the input and the target assembly times and market values. Using the trained predictive model information and the new set of product complexities, the ANNs were then tested on five of the remaining products. Each neural network is made up of 189 architectures with 100 repetitions each. Hence, the training and testing of the ANNs resulted in 18,900 individual performance value estimates. The precision analysis results of the18,900 estimates for the five test products in each of the four prediction models are presented in Section 3.2.

3.2 Evaluation of Predictive Precision

The test product set used for predicting the performance value estimates comprises of the sander, hair dryer, lawn mower, flashlight, and food chopper. The predictive precision analysis is conducted for four prediction models; two of which estimate assembly time in seconds and the other two estimate market value in US dollar ($). This results in a total of four sets of performance value estimates. The standard deviation of the absolute percentage error is computed to measure the predictive precision of the four prediction models. The mathematical formulae used in the measurement of predictive precision are illustrated in Section 3.2.1.

3.2.1 Precision measurement

In order to measure predictive precision, the error in estimated performance values must first be evaluated. The predictive error is given by the difference between the estimated and the target performance value. This can be calculated using equation 12 as shown below.

$$\text{Predictive Error} = \left|(Performance\ Estimate - Performance\ Target)\right| \qquad (12)$$

Since two types of performance values (assembly time and market value) are estimated using the four prediction models, the measure predictive error will not have the same units for all the four prediction models. In order to facilitate an objective comparison of the prediction models, the performance estimates are normalized. This is achieved by calculating the percentage predictive error, which is the percentage value of the ratio of the predictive error and the performance target value. The percentage predictive error can be computed using the following mathematical formula:

$$\text{Percentage Predictive Error} = \frac{\text{Predictive Error}}{|Performance\ Target|} \times 100 \qquad (13)$$

Standard deviation is a statistical measure which quantifies the amount of variation in data distribution [69]. It is a measure of the variability of individual observations from the group mean. Thus, the prediction model with the lowest standard deviation value would be the most precise and the model with the highest standard deviation would be the least precise in predicting the performance values. The standard deviation of the percentage predictive error (predictive precision) for the five test products is then evaluated using the mathematical formula (14) presented below.

$$\text{Predictive Precision} = \sqrt{\frac{\sum(\%\ \text{Predictive Error} - \text{Mean}\ \%\ \text{Predictive error})^2}{n}} \tag{14}$$

where,

n = number of estimates

The standard deviation of the percentage predictive error for the five test products across the four prediction models is presented and further analyzed in Section 3.2.2.

3.2.2 Precision Analysis

The precision analysis is conducted for five test products across the four prediction models. The standard deviation of the absolute percentage error is used as the measure to indicate predictive precision. The prediction model with the lowest standard deviation value indicates highest precision in predicting the performance values and vice versa. The four prediction models are each assigned a rank from 1 through 4 depending on the absolute percentage error standard deviation (predictive precision) of the performance estimates. The ranks are assigned in a descending order with rank 1 indicating the highest precision prediction model and rank 4 indicating the prediction model with the lowest precision.

3.2.2.1 Test product 1: Sander

The absolute percentage error of each prediction model for the Sander is computed using the formula (13). Since the ANN gives an output of 18,900 estimates, this results in 18,900 absolute percentage error values for each prediction model. A histogram is used to illustrate the frequency distribution of the percentage errors for each prediction model in Figure 3.6.

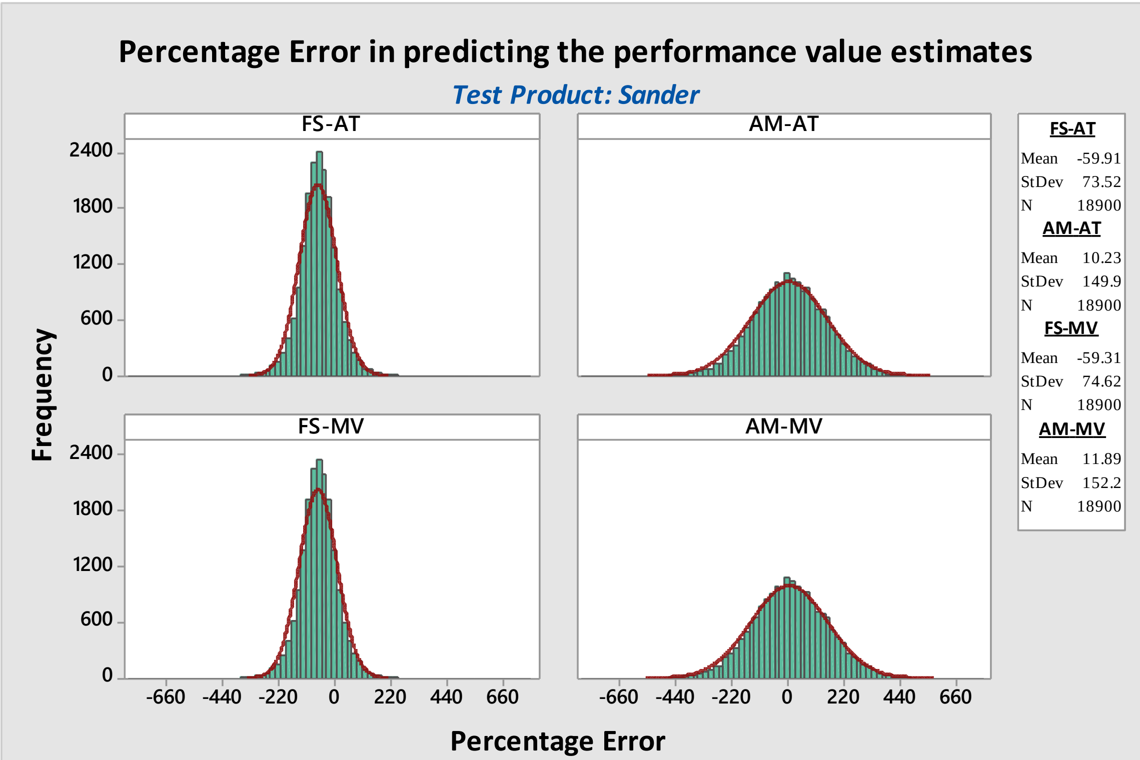


Figure 3.6: Percentage error in prediction for the Sander

In the above figure, the X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors. The normally distributed curves in the above histogram depend on two measures, namely, mean and standard deviation. The mean value determines the position of the center of the curve whereas the standard deviation determines the curve's width and height. It is seen in the figure that the FS-MV and FS-AT prediction models have tall and clustered curves whereas the AM-AT and AM-MV models have short and dispersed curves. This is an indicator that the FS-MV and FS-AT prediction models are more precise as compared to the other two models for the Sander.

The absolute percentage error standard deviation of the performance value estimates and the corresponding ranks for the Sander is illustrated in Table 3.7.

Table 3.7: Precision ranking of the prediction models for the Sander

Prediction Model	Absolute percentage error standard deviation (%)	Rank
FS-AT	73.5	1
AM-AT	149.9	3
FS-MV	74.6	1
AM-MV	152.2	3

A low absolute percentage error standard deviation value indicates high precision and vice versa. Considering that the overall range of the absolute percentage error standard deviation values across the four prediction models is large, the values falling within a $\pm$15% range of each other are assigned equal ranks. The FS-AT and FS-MV prediction models have the lowest absolute % error standard deviation of 73.5% and 74.6% respectively. Both these models are assigned an identical rank of 1 since they differ within a range of $\pm$15% from each other. They are followed by the prediction models AM-AT and AM-MV with absolute % error standard deviations of 149.9% and 152.2% respectively. These two models are also assigned an identical rank of 3 as they fall within the range of $\pm$15%. The test results suggest that the function structures are found to be more precise than the assembly models in predicting the performance value estimates for the sander. The predictive precision rank order of the prediction models for the test product Sander is as follows:

Rank 1: **FS-AT, FS-MV** > Rank 3: **AM-AT, AM-MV**

3.2.2.2 Test product 2: Hair dryer

A histogram is plotted in Figure 3.7 for each prediction model to illustrate the frequency distribution of the percentage errors in prediction for the hair dryer. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

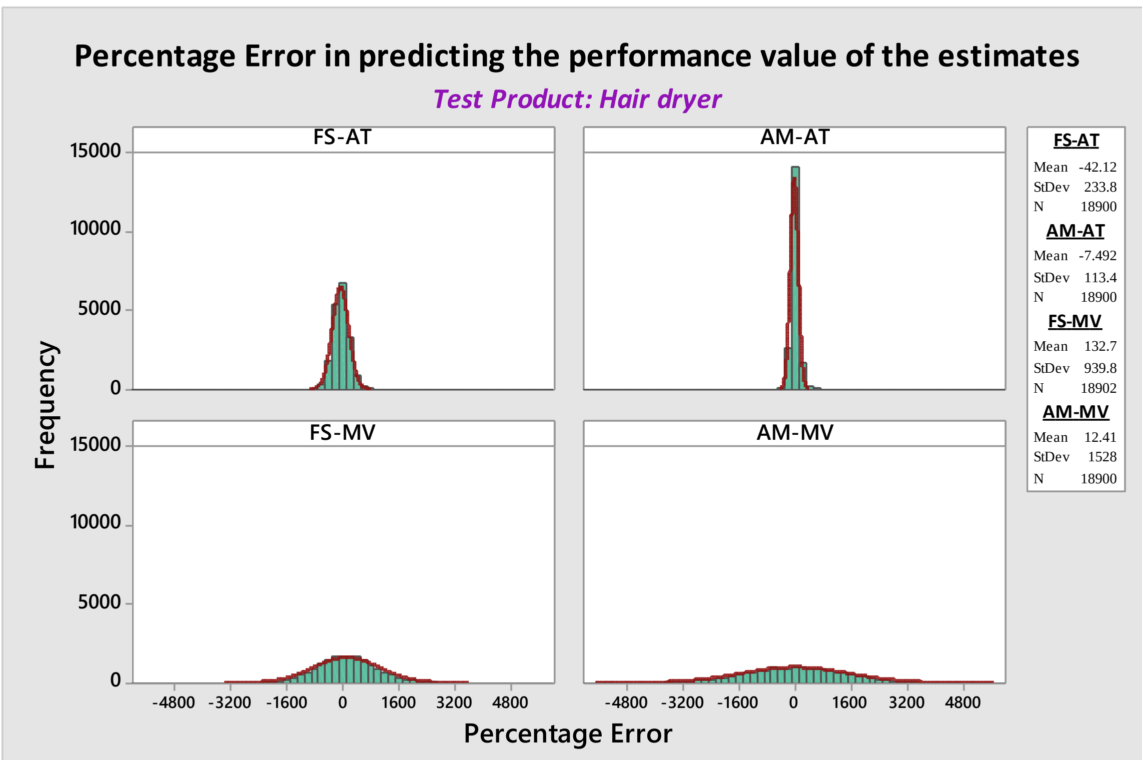


Figure 3.7: Percentage error in prediction for the Hair dryer

In the case of the FS-AT and AM-AT prediction models, it is observed that the percentage errors are closely grouped together as compared to the other two models. This is representative of the fact that the FS-AT and AM-AT prediction models are more precise as compared to the FS-MV and AM-MV models.

The absolute percentage error standard deviation of the performance value estimates and the corresponding ranks for the hair dryer is illustrated in Table 3.8.

Table 3.8: Precision ranking of the prediction models for the Hair dryer

Prediction Model	**Absolute percentage error standard deviation (%)**	**Rank**
FS-AT	233.8	2
AM-AT	113.4	1
FS-MV	939.8	3
AM-MV	1528.0	4

For the hair dryer, it is observed that the AM-AT prediction model has the least absolute percentage error standard deviation of 113.4% and the AM-MV model has the highest absolute percentage error standard deviation of 1528.0%. Hence, these models are ranked 1 and 4 respectively. This is unlike the sander where the AM-AT model ranked 3 in precision. The FS-AT and FS-MV prediction models with absolute percentage error standard deviation values of 233.8% and 939.8% are ranked 2 and 3 respectively. The predictive precision rank order of the prediction models for the hair dryer is as follows:

Rank 1: **AM-AT >** Rank 2: **FS-AT >** Rank 3: **FS-MV >** Rank 4:**AM-MV**

3.2.2.3 Test product 3: Lawn mower

Figure 3.8 illustrates a histogram plot for each prediction model to illustrate the frequency distribution of the percentage errors in prediction for the lawn mower. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

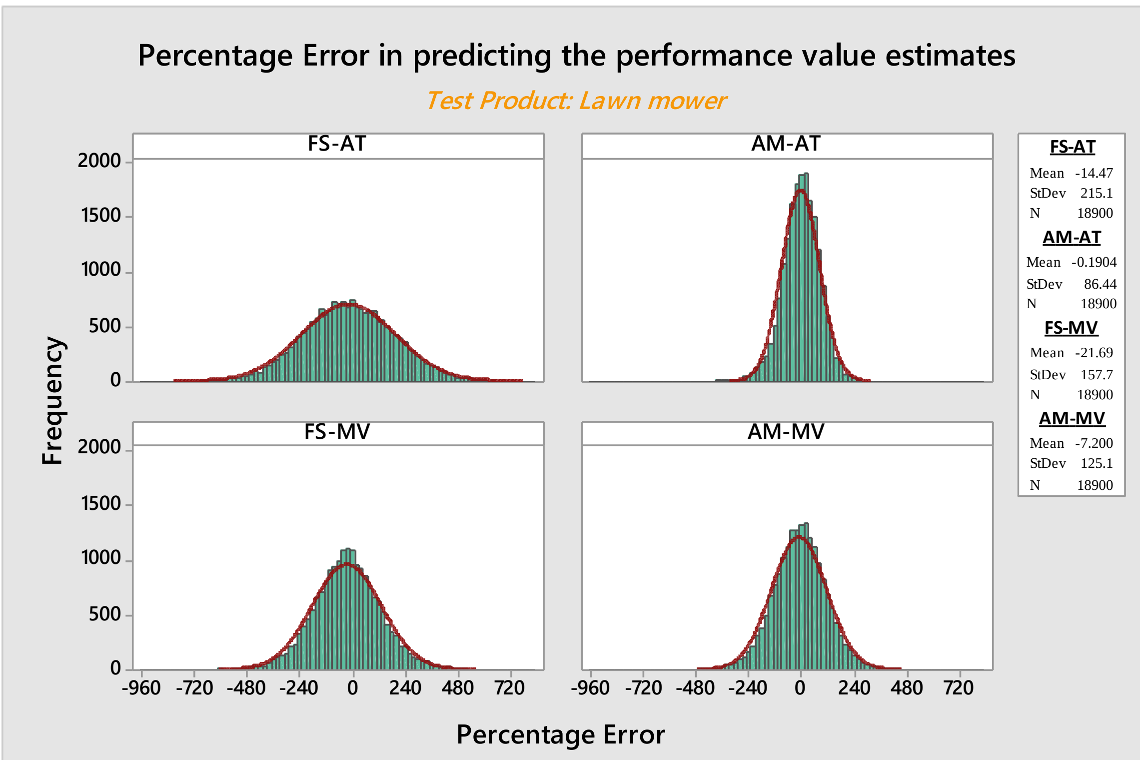


Figure 3.8: Percentage error in prediction for the lawn mower

As seen in the above Figure, the percentage error distribution is the narrowest for the AM-AT prediction model, indicating that it is the most precise prediction model for the lawn mower. The FS-AT model is the most widely distributed amongst the four models and hence, the least precise.

The absolute percentage error standard deviation of the performance value estimates and the corresponding ranks for the lawn mower is illustrated in Table 3.9.

Table 3.9: Precision ranking of the prediction models for the lawn mower

Prediction Model	Absolute percentage error standard deviation (%)	Rank
FS-AT	215.1	4
AM-AT	86.4	1
FS-MV	157.7	3
AM-MV	125.1	2

It is seen that the AM-AT is the most precise model for the lawn mower with an absolute percentage error standard deviation value of 86.4%. It is followed by the models AM-MV, FS-MV, and FS-AT with absolute percentage error standard deviation values of 125.1%, 157.7%, and 215.1% respectively. An observation of interest is that the assembly model representation is more precise as compared to the function structures in estimating the performance values for the lawn mower. This is unlike the sander where the function structures were found to be more precise than the assembly models. The predictive precision rank order of the prediction models for the lawn mower is as follows:

Rank 1: **AM-AT** > Rank 2: **AM-MV** > Rank 3: **FS-MV** > Rank 4: **FS-AT**

3.2.2.4 Test product 4: Flashlight

A histogram is plotted in Figure 3.9 to illustrate the frequency distribution of the percentage errors in prediction for the flashlight. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

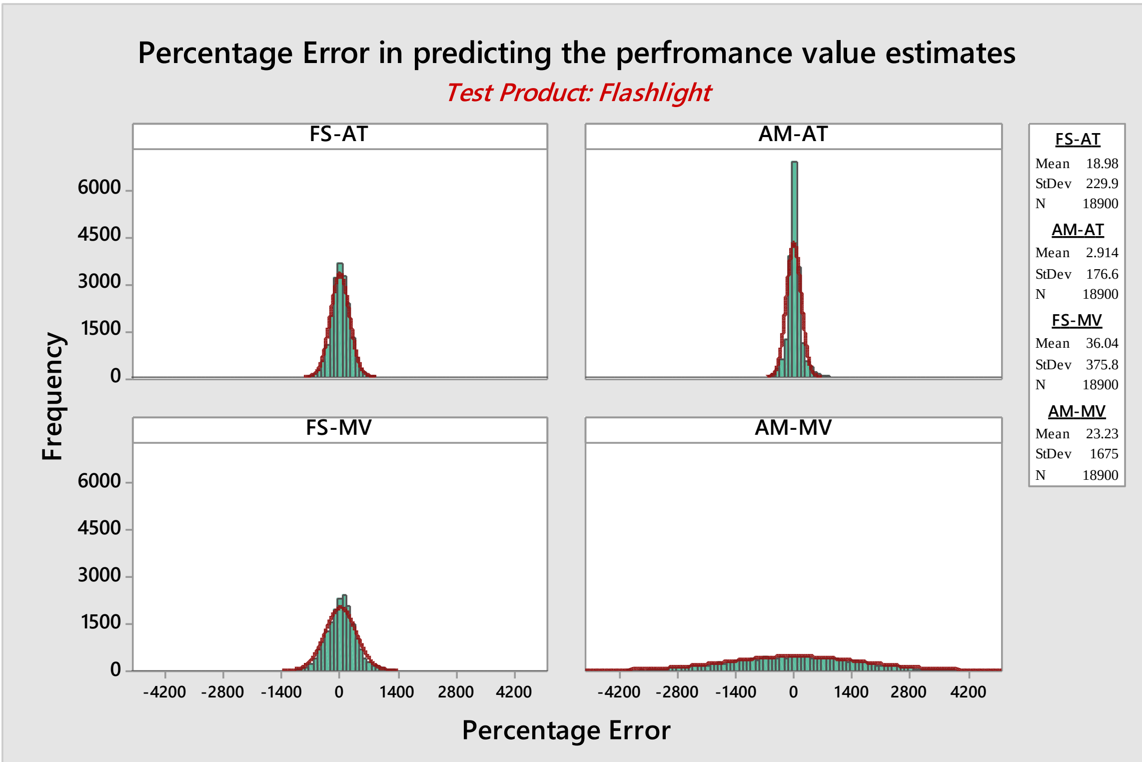


Figure 3.9: Percentage error in prediction for the flashlight

As seen in the above figure, the percentage error distribution is the narrowest for the AM-AT prediction model, indicating that it is the most precise prediction model for the flashlight. The AM-MV model on the other hand has a widespread distribution indicating that its precision is quite low compared to the other prediction models.

The absolute percentage error standard deviation of the performance value estimates and the corresponding ranks for the flashlight is illustrated in Table 3.10.

Table 3.10: Precision ranking of the prediction models for the flashlight

Prediction Model	Absolute percentage error standard deviation (%)	Rank
FS-AT	229.9	2
AM-AT	176.6	1
FS-MV	375.8	3
AM-MV	1675.1	4

For the flashlight, it is observed that the AM-AT prediction model has the least absolute percentage error standard deviation of 176.6% and the AM-MV model has the highest absolute percentage error standard deviation of 1675.1%. Hence, these models are ranked 1 and 4 respectively. The FS-AT and FS-MV prediction models with absolute percentage error standard deviation values of 229.9% and 375.8% are ranked 2 and 3 respectively. The precision rank order for the flashlight is the same as that for the hair dryer evaluated earlier. It is as follows:

Rank 1: **AM-AT >** Rank 2: **FS-AT >** Rank 3: **FS-MV >** Rank 4:**AM-MV**

3.2.2.5 Test product 5: Food chopper

Figure 3.10 illustrates a histogram plot for each prediction model of the food chopper. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

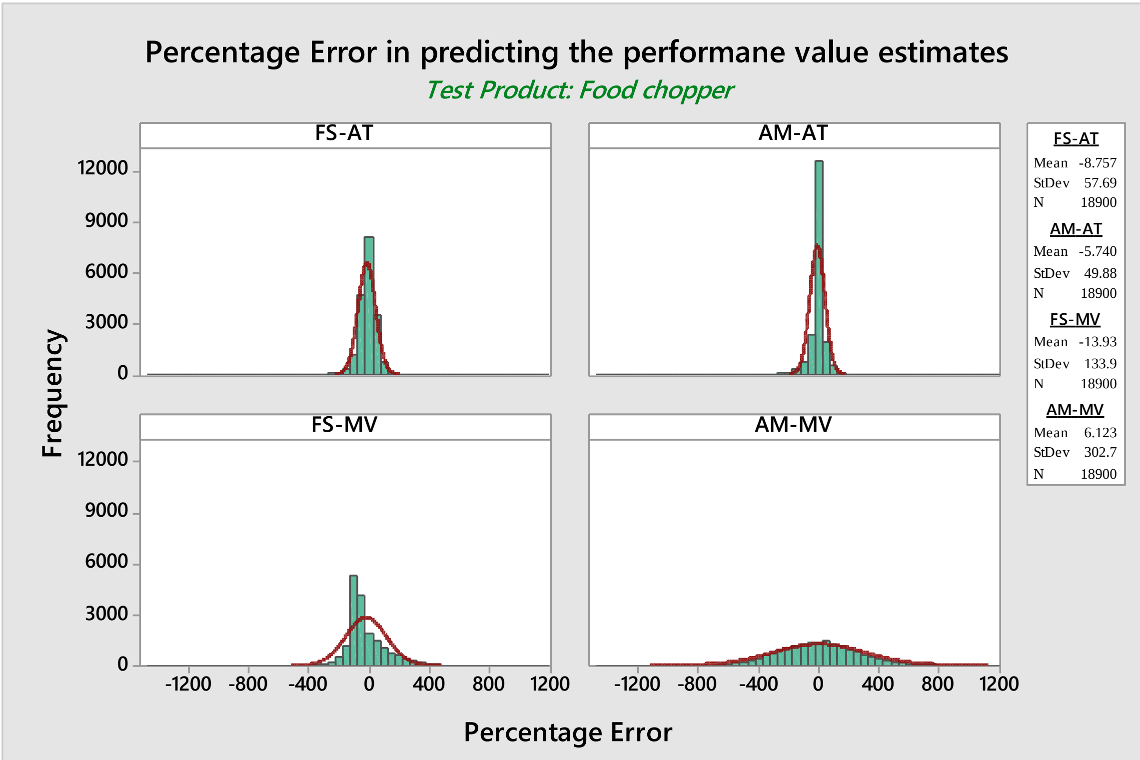


Figure 3.10: Percentage error in prediction for the food chopper

In comparison to the other products the food chopper has closely distributed percentage error values across the four models. The AM-AT model is once again seen to be the most precise with a narrow distribution curve while the AM-MV model is the least precise with a wide distribution curve.

Table 3.11: Precision ranking of the prediction models for the food chopper

Prediction Model	Absolute percentage error standard deviation (%)	Rank
FS-AT	57.7	2
AM-AT	49.9	1
FS-MV	133.9	3
AM-MV	302.7	4

The AM-AT and FS-AT prediction models have absolute percentage error standard deviations of 49.9% and 57.7% respectively. Hence, these models are assigned ranks of 1 and 2 respectively. The FS-MV and AM-MV prediction models with absolute percentage error standard deviation values of 133.9% and 302.7% are ranked 3 and 4 respectively. The precision rank order for the food chopper is as follows:

Rank 1: **AM-AT >** Rank 2: **FS-AT >** Rank 3: **FS-MV >** Rank 4:**AM-MV**

3.3 Predictive Precision Ranking

The purpose of the precision analysis is to determine the performance ranking of the four prediction models for their predictive precision. The analysis is conducted for all the five test products. As seen in the Table 3.12, the AM-AT prediction model is the most precise in predicting the performance values of four of the five products whereas the AM-MV model is the least precise in predicting the performance values of three of the five products. There is however no clear indicator to separate the models FS-AT and FS-MV in terms of individual product ranks. In order to establish a clear rank order for each prediction model; the measures best, worst, mean, and mode ranks for each product are evaluated. The best and worst ranks determine the highest and lowest precision ranks attained by a model for any one of the five products. Mean rank is a measure of the average of the five test product ranks. Mode rank indicates the rank most often scored by a prediction model across the five products.

The predictive precision ranking of the four models for each of the five products is illustrated in Table 3.12.

Table 3.12: Predictive Precision ranking of the prediction models

		FS-AT	**AM-AT**	**FS-MV**	**AM-MV**
1	Sander	1	3	1	3
2	Hairdryer	2	1	3	4
3	Lawnmower	4	1	3	2
4	Flashlight	2	1	3	4
5	Food Chopper	2	1	3	4
	Best Rank	1	1	1	2
	Worst Rank	4	3	3	4
	Mean Rank	2.2	1.4	2.6	3.4
	Mode Rank	2	1	3	4

where,

FS-AT: Function structure - Assembly Time
AM-AT: Assembly model - Assembly Time
FS-MV: Function Structure - Market Value
FS-AT: Function Structure - Assembly Time
Rank 1: highest precision
Ranks 2, 3: intermediate precision
Rank 4: lowest precision

With respect to the measures best and worst rank, a specific rank order cannot be established. However, both mean and mode ranks indicate identical predictive precision rank orders for the four prediction models; which is given as follows:

Rank 1: **AM – AT** > Rank 2: **FS – AT** > Rank 3: **FS– MV** > Rank 4: **AM – MV** (15)

The prediction models are further ranked according to the range of the absolute percentage error standard deviation values for the five products (see Table 3.13). The measure range is the difference between the largest and the smallest percentage error standard deviations. It helps to analyze the extent to which a prediction model precision varies from one product to another.

Table 3.13: Range of absolute % error standard deviation

	FS-AT	**AM-AT**	**FS-MV**	**AM-MV**
Max stdev. (%)	233.8	176.6	939.8	1675.1
Min stdev. (%)	57.7	49.9	74.6	302.7
RANGE (%)	**176.1**	**126.7**	**865.2**	**1372.4**
RANK	**2**	**1**	**3**	**4**

In the above table, the maximum and minimum values of the absolute percentage error standard deviation are used to compute the precision range for each model. There exists a big disparity in the standard deviation range between the AM-AT and FS-AT prediction models and the FS-MV and AM-MV prediction models. The AM-AT model has the best range of 126.7% closely followed by the FS-AT model which has a range of 176.1%. The models FS-MV and AM-MV indicate much higher range values of 865.2% and 1372.4% respectively. These results demonstrate that the AM-AT and FS-AT models predict precisely across all the five test products whereas the precision of the FS-MV and AM-MV models vary extensively from product to product.

The predictive precision rank order based on the measure range is as follows:

Rank 1: **AM – AT >** Rank 2: **FS – AT >** Rank 3: **FS– MV >** Rank 4: **AM – MV** (16)

This rank order is the same as the rank order calculated based on the measures mean and mode. Thus, based on the measures mean, mode, and range the predictive precision rank order of the four prediction models is as illustrated below:

Rank 1: AM-AT Prediction model

Rank 2: FS-AT Prediction model

Rank 3: FS-MV Prediction model

Rank 4: AM-MV Prediction model

Now that the predictive precision rank order is known, it is imperative to comprehend the possible reasons behind this ranking. The AM-AT prediction model utilizes assembly models to predict assembly times. Assembly models contain specific structural information such as component count, connections between these components, and their orientation. These are the fundamental factors which essentially influence the time required to complete a product assembly. This is possibly one of the main driving factors behind the AM-AT prediction model attaining Rank 1. The AM-MV model uses function structures to predict market value. Market value is predominantly determined on the basis of the product's functional abilities rather than its assembly details. This is reflected in the precision rank order with the FS-MV prediction model proving to be a better indicator of market value as compared to the AM-MV model.

3.4 Comparative evaluation of the prediction models based on accuracy and precision

This section demonstrates the predictive accuracy and precision of the engineering design representations (assembly models and function structures) in predicting the performance value estimates (assembly time and market value). Previous research compared the four prediction models and assigned ranks based on the accuracy of their prediction [8]. In section 3.3 of this thesis, the models were analyzed and assigned ranks based on their predictive precision. Table 3.14 illustrates the rank order of the prediction models with respect to both predictive precision and accuracy.

Table 3.14: Predictive accuracy and precision rank order

Prediction model	Accuracy Rank [8]	Precision Rank
Assembly Model - Assembly Time	1	1
Assembly Model - Market Value	2	4
Function Structure - Assembly Time	3	2
Function Structure - Market Value	4	3

As seen in Table 3.14, the Assembly Model - Assembly Time (AM-AT) prediction model is ranked 1 for both predictive accuracy and precision. This reflects that given assembly models, the GCCM can consistently predict accurate assembly times; thus indicating the robustness of the Assembly Model - Assembly Time prediction model. The Function Structure - Assembly Time prediction model is ranked 3 for accuracy and 2 for its precision whereas the Function Structure - Market Value prediction model ranked 4 for its accuracy and 3 for precision. The Assembly Model - Market Value (AM-MV) prediction model is ranked 2 for its predictive accuracy but ranked 4 for its precision which demonstrates that it is accurate in predicting the performance values but not with enough consistency. This lack of precision could be due to the fact that the assembly models do not contain information regarding all the factors that contribute towards a product's market value. For instance, information such as product material, labor cost, manufacturing cost etc. which factor in a product's market value are not contained in assembly models.

A critical observation of interest is that amongst the five test products, the food chopper predicts the performance value estimates within an accuracy range of 5.74% to 13.93% and within a standard deviation range of 49.88% to 302.7%. It is by far the most accurate and precise as compared to the other consumer products. One can hypothesize that this is due to the use of similar architecture products in the training set, namely, the blender, juice extractor, and food mixer. Additional experimentation can be done using a larger population of similar product architectures in the training set in order to further improve the GCCM's predictive performance.

Chapter Four
SENSITIVITY ANALYSIS OF THE COMPLEXITY METRICS

The Graph Complexity Connectivity Method (GCCM) currently employs twenty nine complexity metrics divided across four classes as the input to train the artificial neural networks (ANNs). These metrics were developed and integrated into the method over time with the objective to evaluate system complexity and create surrogate prediction models of assembly time and market value, given assembly models and function structures. However, the influence of each metric in predicting the performance values across all the four surrogate prediction models is undetermined. The objective of the sensitivity analysis conducted in this chapter is to identify the influential (significant) complexity metrics in the estimation of the performance values, assembly time and market value.

Multiple linear regression is the statistical technique used to conduct the sensitivity analysis of the twenty nine complexity metrics in performance value prediction for the four prediction models. This technique is used owing to its ability to model the impact of multiple explanatory variables (independent variables) in predicting the response variable (dependent variable). In the sensitivity analysis, the twenty nine complexity metrics represent the explanatory variables and the performance value represents the response variable. The sensitivity analysis of the metrics as predictors through the ANNs can also help us avoid the limitation of the low data set size associated with the high degree of freedom of the 29 complexity metrics.

The significant metrics identified using the regression analysis for each of the four prediction models are further used to train and test the ANNs to predict the product performance values. This is followed by a comparative evaluation of predictive accuracy and precision of the performance value estimates evaluated using both the original set of twenty nine metrics and the new set of significant metrics.

4.1 Analysis procedure

The statistical program Minitab (version 17.1.0) is used for the multiple linear regression analysis. The specifications of the computer employed for the analysis are as follows:

Windows edition: 8.1 machine

Processor: 2.40 GHz,

Installed memory (RAM): 8GB,

Operating System type: 64-bit.

The analysis settings for the Minitab analysis are found in Table 4.1.

Table 4.1: Minitab analysis parameters

Analysis:	Multiple Linear Regression
Method:	Stepwise
Confidence for all intervals:	90%
Type of confidence interval:	Two-sided
Sum of squares for tests:	Adjusted
Box Cox Transformation:	None

The twenty nine complexity metrics are used as the explanatory variables (independent variables) and the 18,900 performance value estimates are used as the response variables (dependent variables) for the stepwise multiple linear regression analysis of the 15 training products. Stepwise regression methodically adds the most significant variable or removes the least significant variable during each step. The three common procedures for stepwise regression include forward selection, backward elimination and the standard stepwise selection procedure. Forward selection starts with no predictors in the model with the most significant variable being added in each step. Backward elimination starts with all predictors in the model with the least significant variable being eliminated in each step. The standard stepwise selection procedure is a combination of the forward selection and backward elimination procedures. After each step in which a variable is added, all the applicant variables in the model are inspected to see if their significance has been reduced below the specified tolerance level. Hence, the standard stepwise variable selection procedure is selected for this analysis. Due to a small sample size comprising of five test products and fifteen training products, a wide confidence interval of 90% is used.

In this analysis, the 'Alpha-to-enter value' of 0.1 is used as the specified tolerance level. If a non-significant variable is found, it is removed from the model. The 'Alpha-to-remove' value of 0.1 is used as the indicator for a variable's significance. The adjusted sums of squares is used in this analysis as it does not depend on the order in which the factors are entered into the regression model as opposed to the sequential sum of squares. The results from the analysis are illustrated in Section 4.2.

4.2 Results of the sensitivity analysis

The stepwise multiple linear regression analysis is conducted to identify the significant complexity metrics in the prediction of performance value estimates (significant predictors). This results in four sets of significant predictors, one for each prediction model. The significant predictors involved in the FS-AT prediction model are illustrated in Table 4.2. The column Metric # represents the number corresponding to each metric as assigned earlier in Table 3.4.

Table 4.2: Significant predictors in the FS-AT prediction model

Class	Type: Metric	Metric #	Coefficient	p-value
Size	Dimensional: Elements	m1	10.02	0.000
Size	Connective: Connections	m4	2.96	0.018
Interconnection	Flow rate: Sum	m9	-0.411	0.001
Interconnection	Flow rate: Max	m10	-5.86	0.001
Interconnection	Flow rate: Mean	m11	-13.60	0.088
Interconnection	Flow rate: Density	m12	783	0.000
Centrality	Betweenness: Max	m14	0.2587	0.001
Decomposition	Core numbers In: Density	m25	1313	0.005
Decomposition	Core numbers Out: Density	m29	-2133	0.000

where,

m: Complexity Metric

Nine out of the twenty nine complexity metrics are significant predictors for the FS-AT prediction model. The other complexity metrics are removed from the model because their p-values are greater than the 'Alpha-to-Enter' and 'Alpha-to-remove' values of 0.1. An important point to note is that at least one metric from each of the four classes: Size, Interconnection, Centrality, and Decomposition, is significant in assembly time prediction. Using the coefficients obtained for each significant predictor, the regression equation for the FS-AT prediction model is as follows:

$$\mathit{Assembly\ Time} = -34.0 + 10.02\,\mathrm{m1} + 2.96\,\mathrm{m4} - 0.411\,\mathrm{m9} - 5.86\,\mathrm{m10} - 13.60\,\mathrm{m11} + 783\,\mathrm{m12} + 0.2587\,\mathrm{m14} + 1313\,\mathrm{m25} - 2133\,\mathrm{m29} \quad (17)$$

The complexity metrics that are identified to be significant in the AM-AT prediction model are illustrated in Table 4.3.

Table 4.3: Significant predictors in the AM-AT prediction model

Class	Type: Metric	Metric #	Coefficient	p-value
Size	Dimensional: Elements	m1	0.487	0.036
Interconnection	Shortest path: Sum	m5	0.026	0.000
Interconnection	Shortest path: Density	m8	-361.5	0.000
Interconnection	Flow rate: Mean	m11	-12.522	0.000
Centrality	Clustering Coefficient: Sum	m17	2.486	0.000
Centrality	Clustering Coefficient: Max	m18	-14.29	0.000
Centrality	Clustering Coefficient: Density	m20	-999	0.000
Decomposition	Core numbers In: Sum	m22	0.202	0.073
Decomposition	Core numbers In: Density	m25	148	0.031

where,

m: Complexity Metric

Nine out of the twenty nine complexity metrics are identified as significant predictors for the AM-AT prediction model. A metric from each class is found to be significant with interconnection and centrality being the classes with the most number of significant metrics. The other complexity metrics are removed from the model because their p-values are greater than the 'Alpha-to-Enter' and 'Alpha-to-remove' values of 0.1. Using the coefficients obtained for each significant predictor, the regression equation for the AM-AT prediction model is as follows:

$$Assembly\ \ Time = 141.46 + 0.487\,\mathrm{m1} + 0.026\,\mathrm{m5} - 361.5\,\mathrm{m8} - 12.522\,\mathrm{m11} \quad (18)$$

$$+ 2.486\,\mathrm{m17} - 14.29\,\mathrm{m18} - 999\,\mathrm{m20} + 0.202\,\mathrm{m22} + 148.0\,\mathrm{m25}$$

Table 4.4 depicts the complexity metrics that are influential in estimating market value in the FS-MV prediction model.

Table 4.4: Significant predictors in the FS-MV prediction model

Class	Type: Metric	Metric #	Coefficient	p-value
Size	Dimensional: Elements	m1	13.05	0.000
Size	Connective: Connections	m4	1.561	0.044
Interconnection	Flow rate: Sum	m9	-0.296	0.000
Interconnection	Flow rate: Max	m10	-4.74	0.044
Interconnection	Flow rate: Density	m12	741	0.000
Centrality	Betweenness: Sum	m13	0.014	0.002
Decomposition	Core numbers In: Density	m25	1012	0.014
Decomposition	Core numbers Out: Density	m29	-1798	0.000

where,

m: Complexity Metric

For the FS-MV prediction model, eight out of the twenty nine complexity metrics are found to be significant predictors. Using the coefficients obtained for each significant predictor, the regression equation for this prediction model is as follows:

$$Market\ \ Value = -45.7 + 13.05\,\mathrm{m1} + 1.561\,\mathrm{m4} - 0.296\,\mathrm{m9} - 4.74\,\mathrm{m10} \quad (19)$$

$+ 741\ \mathrm{m}12 + 0.014\ \mathrm{m}13 + 1012\ \mathrm{m}25 - 1798\ \mathrm{m}29$

Table 4.4 represents the complexity metrics that are influential in estimating market value in the AM-MV prediction model.

Table 4.5: Significant predictors in the AM-MV prediction model

Class	Type: Metric	Metric #	Coefficient	p-value
Size	Dimensional: Elements	m1	0.476	0.051
Interconnection	Shortest path: Sum	m5	0.026	0.000
Interconnection	Shortest path: Density	m8	-365.6	0.000
Interconnection	Flow rate: Mean	m11	-12.558	0.000
Centrality	Clustering Coefficient: Sum	m17	2.49	0.000
Centrality	Clustering Coefficient: Max	m18	14.37	0.000
Centrality	Clustering Coefficient: Density	m20	-999	0.000
Decomposition	Core numbers In: Sum	m22	0.198	0.079
Decomposition	Core numbers In: Density	m25	150.3	0.026

where,

m: Complexity Metric

It can be seen that an identical set of nine complexity metrics are significant in both the AM-MV and the AM-AT prediction models. This is a clear indicator that the nature of the design representation influences the prediction process more than the nature of the performance values. Using the coefficients obtained for each significant predictor, the regression equation for the AM-MV prediction model is as follows:

$$Market\ \ Value = 141.96 + 0.476\,\mathrm{m1} + 0.026\,\mathrm{m5} - 365.6\,\mathrm{m8} - 12.558\,\mathrm{m11} \quad (20)$$
$$+ 2.49\,\mathrm{m17} + 14.37\,\mathrm{m18} - 999\,\mathrm{m20} + 0.198\,\mathrm{m22} + 150.3\,\mathrm{m25}$$

The significant predictor metrics identified across each of the four prediction models are condensed in Table 4.6 to facilitate comparison. The significant metrics common across the prediction models FS-AT & FS-MV as also the ones which are common across the AM-AT & AM-MV models are italicized. The significant metrics which are common across the FS-AT and AM-AT prediction models as well as the ones common across the FS-MV and AM-MV are underlined. The predictors marked in bold are common for all the four models.

Table 4.6: Significant predictors for the four prediction models

Common predictors: **(bold)**	FS (Common: *italicized*)	AM (Common: *italicized*)
AT (common: underlined)	***m1*** *m4* *m9* *m10* m11 *m12* m14 ***m25*** *m29*	***m1*** *m5* *m8* *m11* *m17* *m18* *m20* *m22* ***m25***
MV (common: underlined)	***m1*** *m4* *m9* *m10* *m12* m13 ***m25*** *m29*	***m1*** *m5* *m8* *m11* *m17* *m18* *m20* *m22* ***m25***

The complexity metrics m1 through m4 belong to the class ‘size’, m5 through m12 fall under the class interconnection, m13 through m20 are associated with the class centrality, and metrics m21 to m29 belong to the class decomposition. The regression analysis suggests that for each design representation, there exists a set of complexity metrics that are significant predictors of performance values. There is at least one metric from each class (size, interconnection, centrality, and decomposition) which is identified as a significant predictor. Two metrics are found to be significant for all the four surrogate prediction models; m1: the number of elements and m25: the density of the in-core numbers.

An observation of interest is that there are more centrality metrics that are significant for the assembly model design representation than for the function structures. This can be elucidated by the fact that the product dataset analyzed comprises of consumer products that are generally designed to be highly modular for ease of manufacturing and assembly. This modularity (or centrality) is not as evident in the function structures.

4.3 Significant metric set prediction results

The four sets of complexity metrics identified as significant predictors for the corresponding four prediction models are now used to train the ANNs. The same set of fifteen consumer products as used before for the original set of twenty nine metrics are used for this ANN training. The trained ANNs are then tested on the same set of five products as before to predict the performance value estimates for each of the four prediction models. Finally, these test results are compared on the basis of predictive accuracy and precision to the earlier test results obtained using the complete set of twenty nine complexity metrics.

4.3.1 Test product: Sander

The absolute percentage error of each prediction model for the Sander is computed using the formula (13). Figure 4.1 illustrates histogram plots for the sander corresponding to the four models, depicting frequency distribution of the percentage errors in prediction.

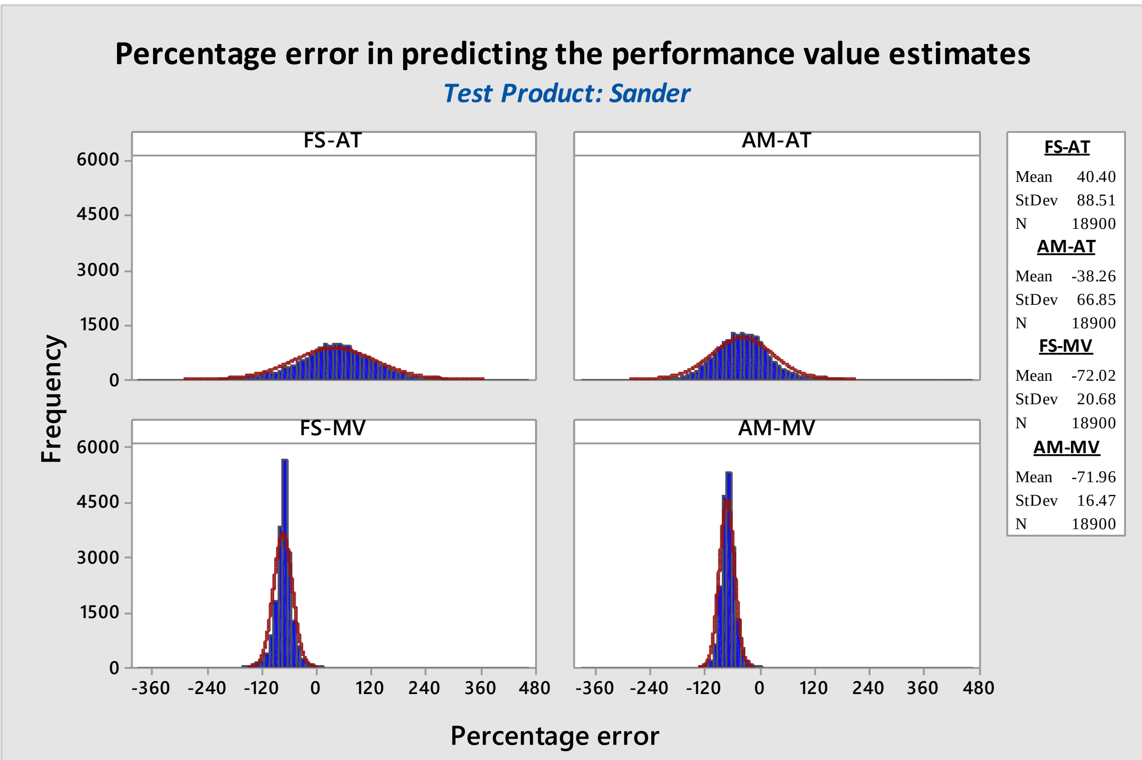


Figure 4.1: Percentage error in prediction for the sander using significant metrics

In the histogram plots, the X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors. The plots suggest that the FS-MV and AM-MV prediction models are more precise but less accurate as compared to the FS-AT and AM-AT models for the Sander. These test results are further compared to the test results obtained using the original set of complexity metrics in Table 4.7. A positive change in error mean and standard deviation indicates that the significant metric set predicts with higher accuracy and precision respectively as compared to the original metric set and vice versa.

Table 4.7: Comparative evaluation of original and significant metrics' estimates for the sander

	Accuracy			Precision		
	Original Absolute Percentage Error Mean (%)	**Significant Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Original Absolute Percentage Error Standard deviation (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	59.91	40.40	**19.51**	73.52	88.51	**-14.99**
AM-AT	10.23	38.26	**-28.03**	149.9	66.85	**83.05**
FS-MV	59.31	72.02	**-12.71**	74.62	20.68	**53.94**
AM-MV	11.89	71.96	**-60.07**	152.2	16.47	**135.73**

The comparative evaluation for the test product sander suggests that using the significant metric set for prediction improves predictive accuracy but decreases precision for the FS-AT prediction model. The opposite is true for the remaining three models.

4.3.2 Test product: Hair dryer

The absolute percentage errors of the prediction models for the hair dryer are computed using the formula (13). Figure 4.2 illustrates histogram plots for the hair dryer corresponding to the four models, depicting frequency distribution of the percentage errors in prediction.

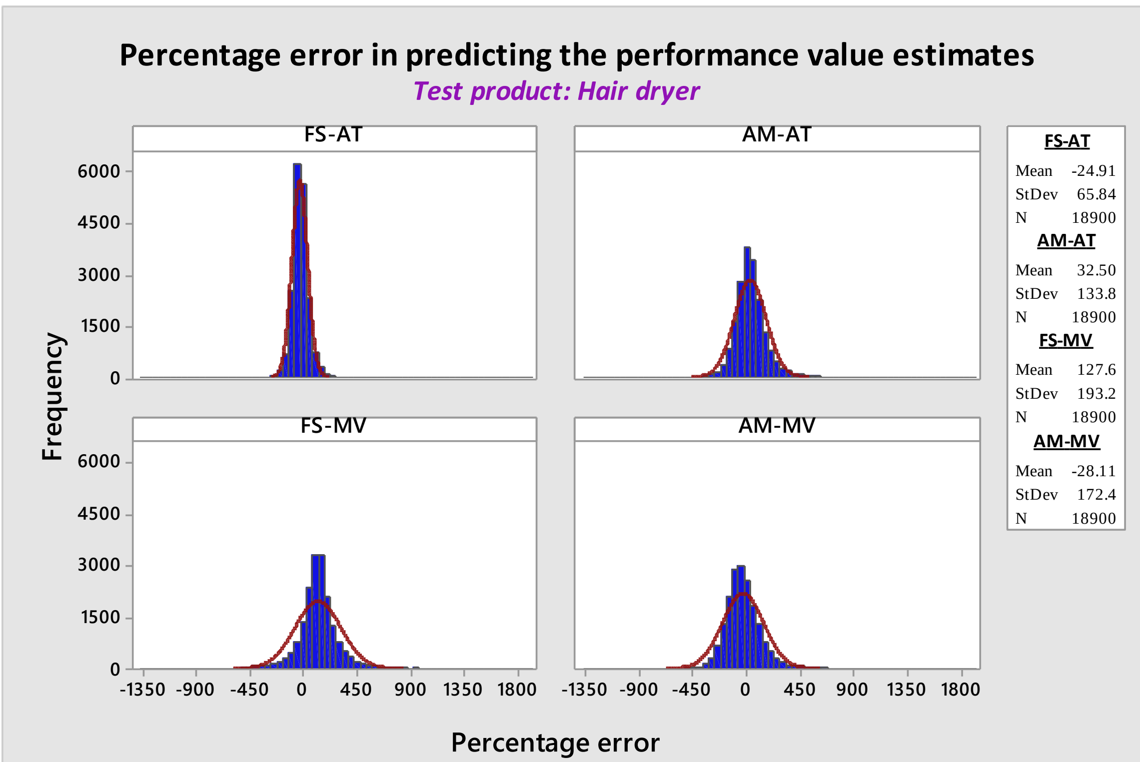


Figure 4.2: Percentage error in prediction for hair dryer using significant metrics

The X-axis of the histograms represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors. The histograms suggest that the FS-AT prediction model is the most accurate and precise in prediction. These test results are further compared to the test results obtained using the original set of complexity metrics in Table 4.8. A positive change in error mean and standard deviation indicates that the significant metric set predicts with higher accuracy and precision respectively as compared to the original metric set and vice versa.

Table 4.8: Comparative evaluation of the original and significant metrics' estimates for the hair dryer

	Accuracy			Precision		
	Original Absolute Percentage Error Mean (%)	**Significant Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Original Absolute Percentage Error Standard deviation (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	42.12	24.91	**17.21**	233.8	65.84	**167.96**
AM-AT	7.49	32.50	**-25.01**	113.4	133.8	**-20.4**
FS-MV	132.7	127.6	**5.1**	939.8	193.2	**746.6**
AM-MV	12.41	28.11	**-15.7**	1528	172.4	**1355.6**

The comparative evaluation for the test product hair dryer suggests that using the significant metric set for prediction improves predictive accuracy only for the FS-AT and FS-MV prediction models. The predictive precision is seen to improve for the FS-AT, FS-MV and AM-MV prediction models when the significant metric set is used.

4.3.3 Test product: Lawn mower

The absolute percentage error of each prediction model for the lawn mower is computed using the formula (13). Figure 4.3 illustrates histograms for the lawn mower corresponding to the four models, depicting frequency distribution of the percentage errors in prediction.

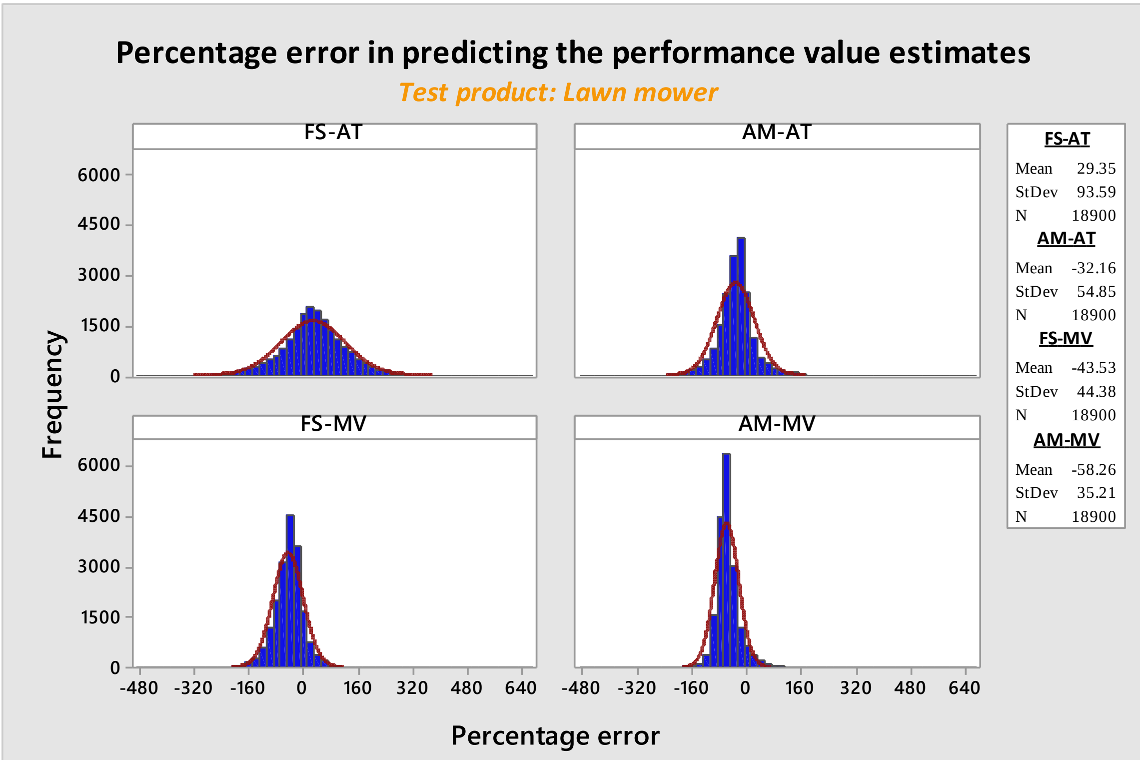


Figure 4.3: Percentage error in prediction for lawn mower using significant metrics

The X-axis of the histograms represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors. The histograms suggest that the FS-MV and AM-MV prediction models are more precise but less accurate as compared to the FS-AT and AM-AT models for the hair dryer. These test results are further compared to the test results obtained using the original set of complexity metrics in Table 4.9. A positive change in error mean and standard deviation indicates that the significant metric set predicts with higher accuracy and precision respectively as compared to the original metric set and vice versa.

Table 4.9: Comparative evaluation of the original and significant metrics' estimates for the lawn mower

	Accuracy			Precision		
	Original Absolute Percentage Error Mean (%)	**Significant Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Original Absolute Percentage Error Standard deviation (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	14.47	29.35	**-14.88**	215.1	93.59	**121.51**
AM-AT	0.19	32.16	**-31.97**	86.44	54.85	**31.59**
FS-MV	21.69	43.53	**-21.84**	157.7	44.38	**113.32**
AM-MV	7.2	58.26	**-51.06**	125.1	35.21	**89.89**

The comparative evaluation for the test product lawn mower suggests that using the significant metric set for prediction improves predictive precision but reduces predictive accuracy for all the four prediction models.

4.3.4 Test product: Flashlight

The absolute percentage error of each prediction model for the flashlight is computed using the formula (13). Figure 4.4 illustrates histograms of the flashlight corresponding to the four models. These depict the frequency distribution of the percentage errors in prediction.

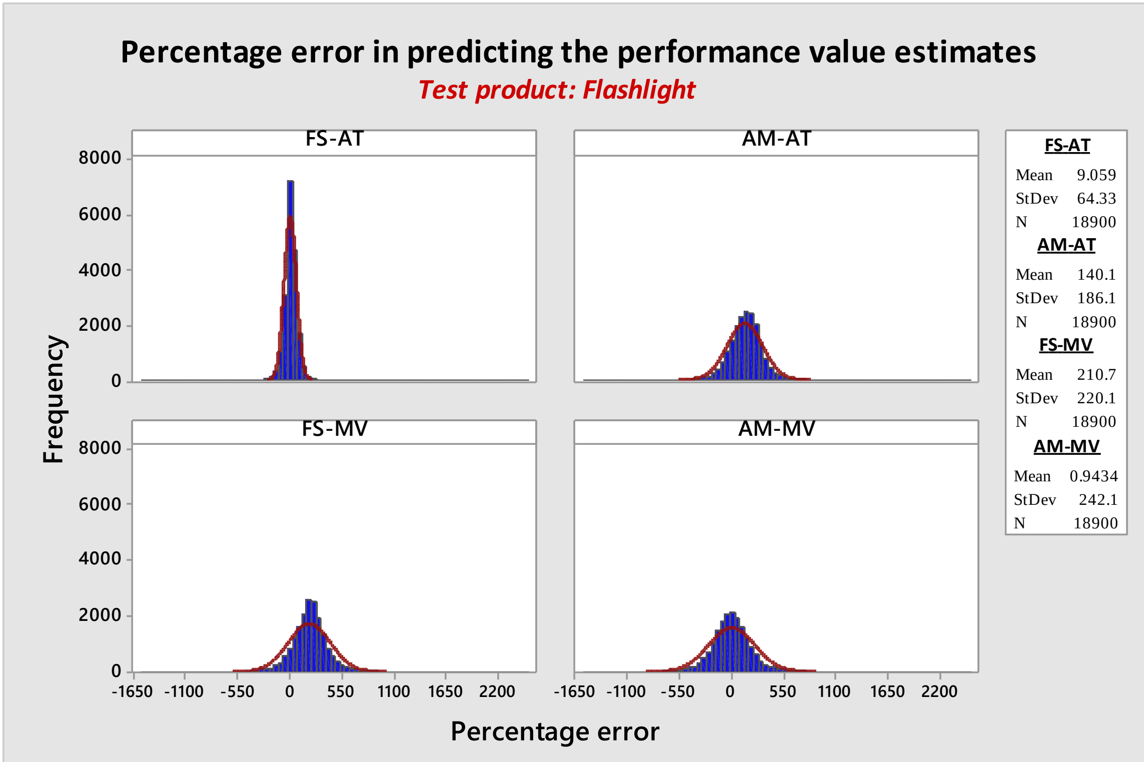


Figure 4.4: Percentage error in prediction for the flashlight using significant metrics

The X-axis of the histograms represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors. The histograms suggest that the FS-MV and AM-MV prediction models are more precise but less accurate as compared to the FS-AT and AM-AT models for the flashlight. These test results are further compared to the test results obtained using the original set of complexity metrics in Table 4.10. A positive change in error mean and standard deviation indicates that the significant metric set predicts with higher accuracy and precision respectively as compared to the original metric set and vice versa.

Table 4.10: Comparative evaluation of the original and significant metrics' estimates for the flashlight

	Accuracy	Precision

	Original Absolute Percentage Error Mean (%)	Significant Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Original Absolute Percentage Error Standard deviation (%)	Significant Absolute Percentage Error Standard deviation (%)	Change in Error Standard deviation (%)
FS-AT	18.98	9.06	**9.92**	229.9	64.33	**165.57**
AM-AT	2.91	140.1	**-137.19**	176.6	186.1	**-9.5**
FS-MV	36.04	210.7	**-174.66**	375.8	220.1	**155.7**
AM-MV	23.23	0.94	**22.29**	1675	242.1	**1432.9**

The comparative evaluation for the test product flashlight suggests that using the significant metric set for prediction improves predictive accuracy only for the FS-AT and AM-MV prediction models. On the other hand, the predictive precision is seen to improve for the FS-AT, FS-MV and AM-MV prediction models when the significant metric set is used.

4.3.5 Test product: Food chopper

The absolute percentage error of each prediction model for the food chopper is computed using the formula (13). Figure 4.5 illustrates histograms for the food chopper corresponding to the four models, depicting frequency distribution of the percentage errors in prediction.

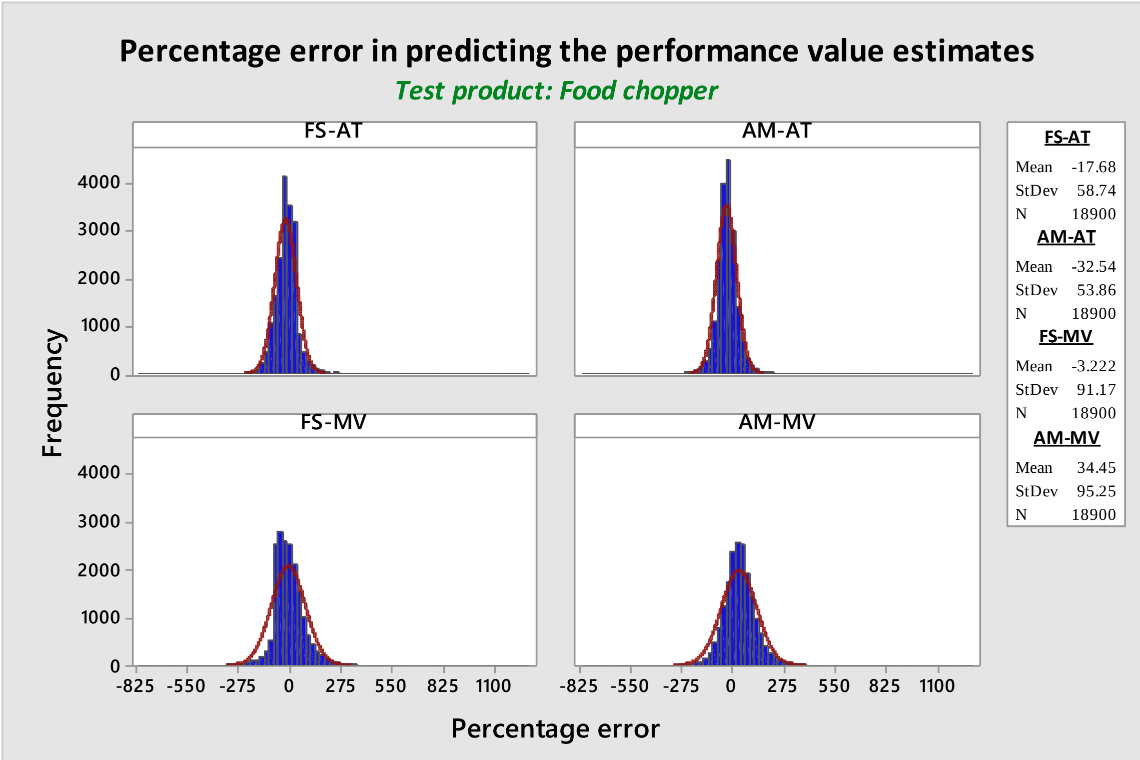


Figure 4.5: Percentage error in prediction for food chopper using significant metrics

The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors. The histograms suggest that the FS-MV and AM-MV prediction models are more precise but less accurate as compared to the FS-AT and AM-AT models for the food chopper. These test results are further compared to the test results obtained using the original set of complexity metrics in Table 4.11. A positive change in error mean and standard deviation indicates that the significant metric set predicts with higher accuracy and precision respectively as compared to the original metric set and vice versa.

Table 4.11: Comparative evaluation of the original and significant metrics' estimates for the food chopper

	Accuracy	Precision

	Original Absolute Percentage Error Mean (%)	Significant Absolute Percentage Error Mean (%)	Change in Error Mean (%)	Original Absolute Percentage Error Standard deviation (%)	Significant Absolute Percentage Error Standard deviation (%)	Change in Error Standard deviation (%)
FS-AT	8.76	17.68	**-8.92**	57.69	58.74	**-1.05**
AM-AT	5.74	32.54	**-26.8**	49.88	53.86	**-3.98**
FS-MV	13.93	3.22	**10.71**	133.9	91.17	**42.73**
AM-MV	6.12	34.45	**-28.33**	302.7	95.25	**207.45**

The comparative evaluation for the test product food chopper suggests that using the significant metric set for prediction improves predictive accuracy only for the FS-MV prediction models. The predictive precision increases for the FS-MV and AM-MV prediction models when the significant metric set is used.

4.3.6 Conclusions from the prediction results

The test results suggest that on the whole the precision of the prediction models increases when the significant metric set is used for prediction instead of the complete set of twenty nine complexity metrics. This is an indicator that employing only the significant sets of complexity metrics for prediction improves the Graph Complexity Connectivity Method's ability to produce consistent results under the same conditions.

There is however a decrease in the predictive accuracy of most of the prediction models while using the significant metrics. These results indicate that further work needs to be conducted in an attempt to shift these precise measurements towards the target value. This can be achieved by training and testing the artificial neural networks using consumer products that have similar product architectures or those from within the same category of consumer products. For instance, exclusive use of products those fall under the category of consumer power tools. Previous research has indicated that the predictive accuracy increases when products from within the same category are used to estimate assembly times, given assembly models [15]. The confidence intervals used for the regression analysis can also be modified in an effort to improve the accuracy of prediction.

In spite of their relatively low prediction accuracy, these significant complexity metrics can still prove to be valuable predictors of later stage information considering the fact that they are evaluated using early design stage representations. It is important to note that in the early design stage, the product structural information available is minimal. Hence, these early design stage significant metrics with relatively low accuracy can be as valuable as the metrics evaluated using a more detailed design representation with higher accuracy in predicting the same information. These significant metrics will enable designers to consider the impacts of their decisions in the early design stage using exact quantifiers rather than subjective judgments. This can eventually lead to cost savings by making more informed decisions earlier in the design process.

Chapter Five
EXPERIMENTATION WITH DIFFERENT SETS OF SIGNIFICANT METRICS

In this chapter, the identified significant complexity metrics for the four prediction models are divided into different experimental sets which are then used to train and test the ANNs. These experimental sets would essentially contain the union and intersection of the identified significant complexity across the four prediction models. The ANN test estimates are further examined for predictive accuracy and precision. These experiments will enable us to investigate the effect of manipulation of the significant complexity metrics and in turn answer research question 3.

5.1 Experiment setup

In the previous chapter, four sets of complexity metrics were determined to be significant (influential) predictors of performance values for the corresponding four prediction models. The significant complexity metric sets for the FS-AT, AM-AT, and AM-MV prediction models consist of nine metrics each whereas the significant metric set for the FS-MV prediction model consists of eight metrics. The dataset for experiment 1 consists of the union of the metrics significant across both the FS-AT and FS-MV models. Experiment 2 includes the significant metrics that are common among the FS-AT and FS-MV models. The metrics identified to be significant predictors for the AM-AT and AM-MV prediction models are identical. The union and intersection sets of these metrics would result in the same set of metrics. This is the reason why experiments 1 and 2 are not conducted for the AM-AT and AM-MV models. Finally, experiment 3 is conducted for a comprehensive set involving the union of all the significant metrics across each of the four prediction models.

5.2 Experiment 1: Union of FS-AT and FS-MV significant metric sets

The significant complexity metrics of the FS-AT and FS-MV prediction models are combined to form the complexity metric vector for this experiment. This complexity vector is then used to train and test the ANNs for the same set of consumer products as for the previous analyses.

5.2.1 Test product: Sander

Figure 5.1 illustrates histogram plots for the sander corresponding to the four models, depicting frequency distribution of the percentage errors in prediction.

The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

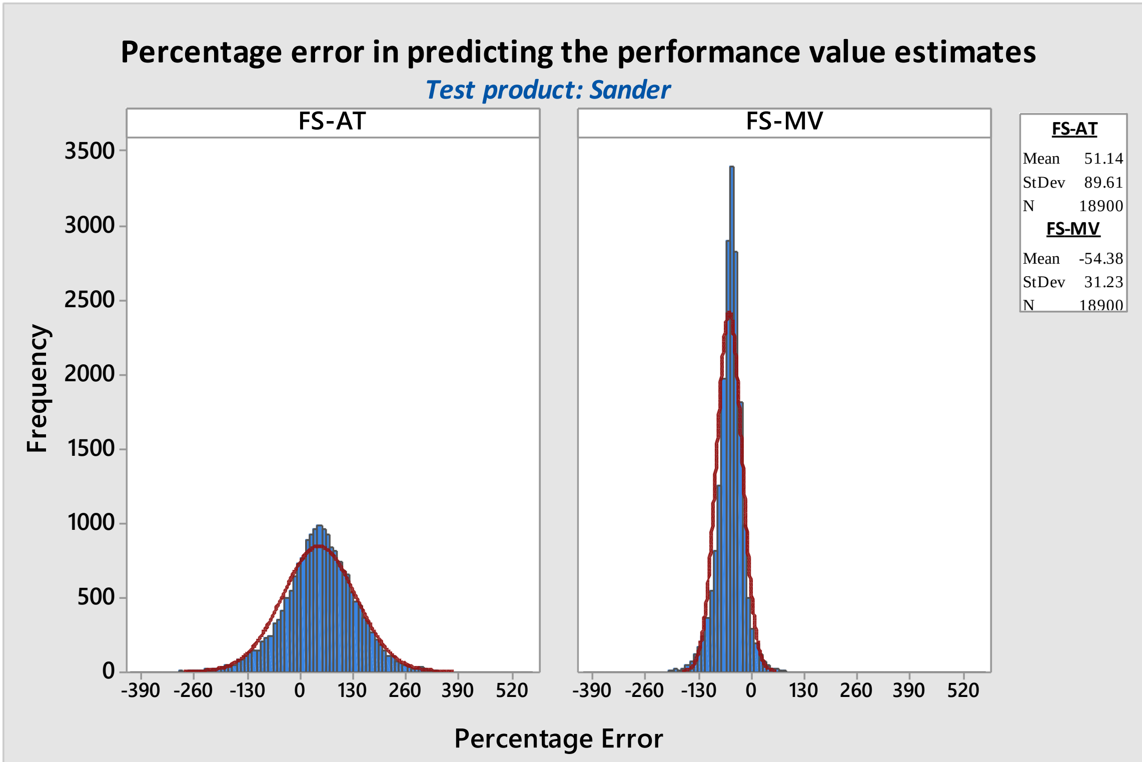


Figure 5.1: Percentage error in prediction for the sander for experiment 1

The absolute values of the percentage error means are similar for the two prediction models. However, the FS-MV model has a narrower distribution as compared to the FS-AT model, indicating that the FS-MV model is more precise. In Table 5.1, the percentage error mean and standard deviation of the performance estimates obtained for experiment 1 are compared to the results evaluated earlier in Section 4.3.1 for the significant metric set. A positive change in error mean and standard deviation indicates that the experiment 1 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.1: Comparative evaluation of the significant metric set and experiment 1 estimates for the sander

	Accuracy			Precision		
	Significant Absolute Percentage Error Mean (%)	**Experiment 1 Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Experiment 1 Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	40.40	51.14	**-10.74**	88.51	89.61	**-1.1**
FS-MV	72.02	54.38	**17.64**	20.68	31.23	**-10.55**

The comparative evaluation suggests that experiment 1 predicts with higher accuracy only in the case of the FS-MV prediction model. However, the predictive precision is lower for experiment 1 when compared to the significant metric set.

5.2.2 Test product: Hair dryer

Figure 5.2 illustrates histogram plots for the hair dryer corresponding to the FS-AT and FS-MV prediction models. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

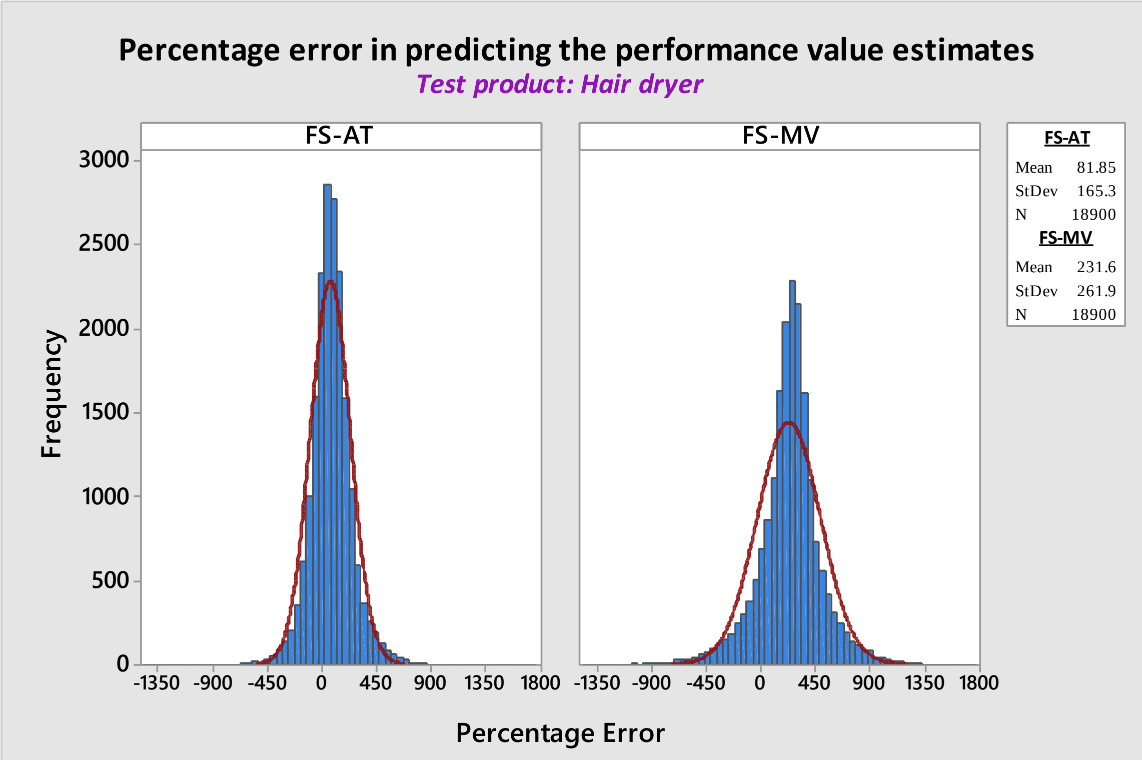


Figure 5.2: Percentage error in prediction for the hair dryer for experiment 1

The FS-AT prediction model is more accurate with an absolute percentage error mean of 81.85% as compared to the FS-MV model which has an absolute percentage error mean of 231.6%. The FS-AT model performs better than the FS-MV model in terms of precision as well with a percentage error standard deviation of 165.3% against the FS-MV model's 261.9%. In Table 5.2, the percentage error mean and standard deviation of the performance estimates obtained for experiment 1 are compared to the results evaluated earlier in Section 4.3.2 for the significant metric set. A positive change in error mean and standard deviation indicates that the experiment 1 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.2: Comparative evaluation of the significant metric set and experiment 1 estimates for the hair dryer

	Accuracy			Precision		
	Significant Absolute Percentage Error Mean (%)	**Experiment 1 Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Experiment 1 Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	24.91	81.85	**-56.94**	65.84	165.3	**-99.46**
FS-MV	127.6	231.6	**-104.00**	193.2	261.9	**-68.70**

The comparative evaluation suggests that experiment 1 predicts with lower accuracy and precision in the case of both FS-AT and FS-MV prediction models. This suggests that for the hair dryer, the predictive accuracy and precision is better when the respective sets of significant metrics identified for the two models are used for prediction.

5.2.3 Test product: Lawn mower

Figure 5.3 depicts histogram plots for the lawn mower corresponding to the FS-AT and FS-MV prediction models. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

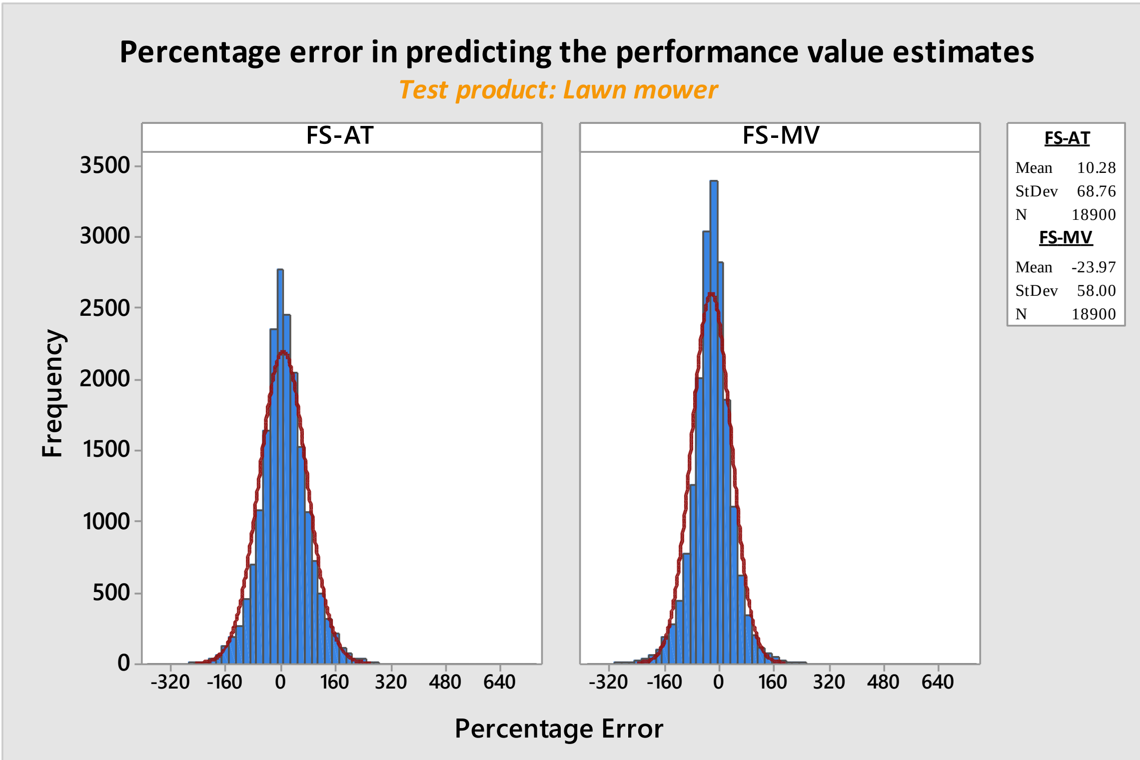


Figure 5.3: Percentage error in prediction for the lawn mower for experiment 1

The FS-AT prediction model is more accurate with an absolute percentage error mean of 10.28% as compared to the FS-MV model which has an absolute percentage error mean of 23.97%. However, the FS-MV model performs better than the FS-AT model in terms of precision with a percentage error standard deviation of 58.00% against the FS-AT model's 68.76%. In Table 5.3, the percentage error mean and standard deviation of the performance estimates obtained for experiment 1 are compared to the results evaluated earlier in Section 4.3.3 for the significant metric set. A positive change in error mean and standard deviation indicates that the experiment 1 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.3: Comparative evaluation of the significant metric set and experiment 1 estimates for the lawn mower

	Accuracy			Precision		
	Significant Absolute Percentage Error Mean (%)	**Experiment 1 Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Experiment 1 Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	29.35	10.28	**19.07**	93.59	68.76	**24.83**
FS-MV	43.53	23.97	**19.56**	44.38	58.00	**-13.62**

The comparative evaluation suggests that experiment 1 predicts with higher accuracy in the case of both FS-AT and FS-MV prediction models. The predictive precision is lower for experiment 1 when compared to the significant metric set for the FS-MV model.

5.2.4 Test product: Flashlight

Figure 5.4 illustrates histogram plots for the flashlight corresponding to the FS-AT and FS-MV prediction models. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

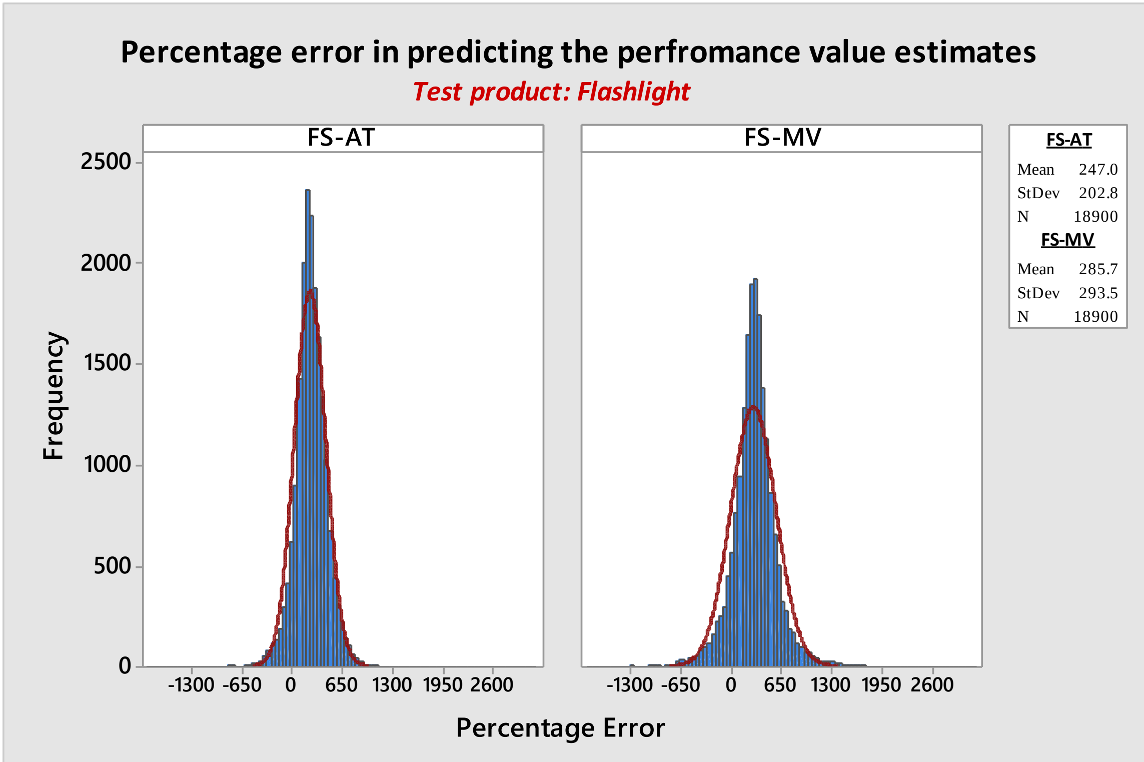


Figure 5.4: Percentage error in prediction for the flashlight for experiment 1

The FS-AT prediction model is more accurate with an absolute percentage error mean of 247.0% as compared to the FS-MV model which has an absolute percentage error mean of 285.7%. The FS-AT model performs better than the FS-MV model in terms of precision as well with a percentage error standard deviation of 202.8% against the FS-MV model's standard deviation of 293.5%. In Table 5.4, the percentage error mean and standard deviation of the performance estimates obtained for experiment 1 are compared to the results evaluated earlier in Section 4.3.4 for the significant metric set. A positive change in error mean and standard deviation indicates that the experiment 1 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.4: Comparative evaluation of the significant metric set and experiment 1 estimates for the flashlight

	Accuracy			Precision		
	Significant Absolute Percentage Error Mean (%)	**Experiment 1 Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Experiment 1 Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	9.06	247.0	**-237.94**	64.33	202.8	**-138.47**
FS-MV	210.7	285.7	**-75**	220.1	293.5	**-73.4**

The comparative evaluation suggests that experiment 1 predicts with lower accuracy and precision in the case of both FS-AT and FS-MV prediction models. This suggests that for the flashlight, the predictive accuracy and precision is better when the respective sets of significant metrics identified for the two models are used for prediction.

5.2.5 Test product: Food chopper

Figure 5.5 illustrates histogram plots for the food chopper corresponding to the FS-AT and FS-MV prediction models. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

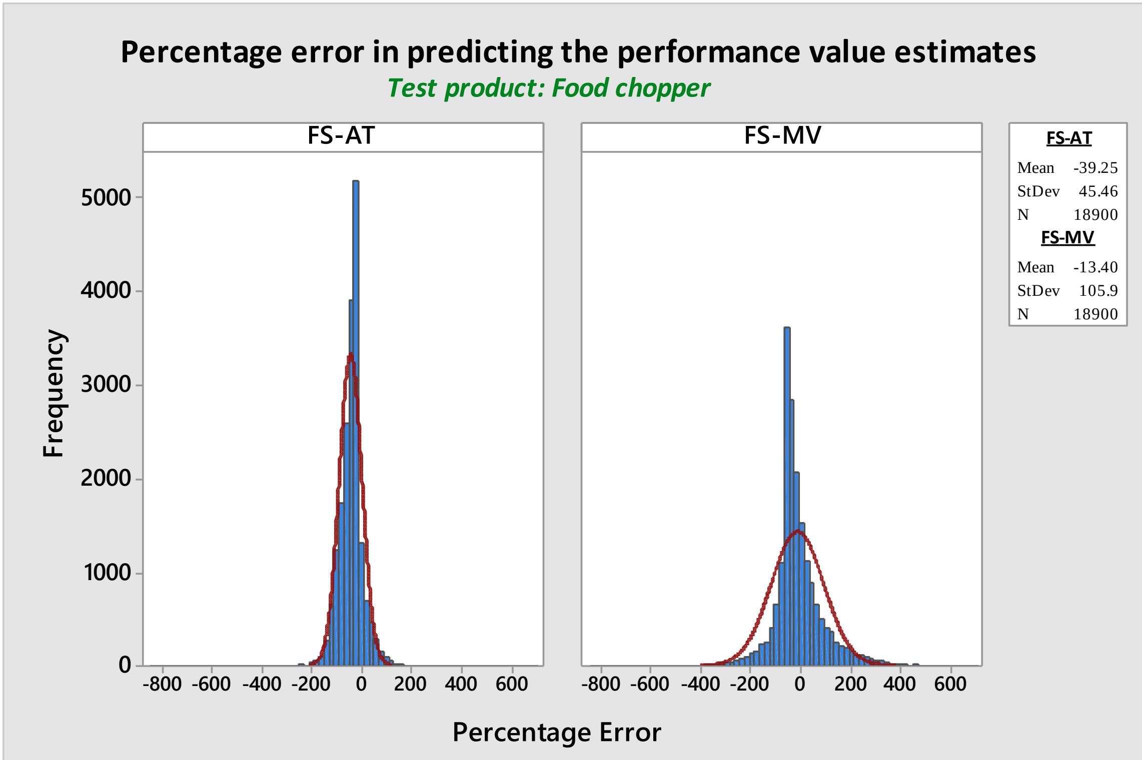


Figure 5.5: Percentage error in prediction for the food chopper for experiment 1

For the food chopper, the FS-MV prediction model is more accurate with an absolute percentage error mean of 13.40% as compared to the FS-AT model which has an absolute percentage error mean of 39.25%. However, the FS-AT model performs better than the FS-MV model in terms of precision with a percentage error standard deviation of 45.46% against the FS-MV model's standard deviation of 105.90%. In Table 5.5, the percentage error mean and standard deviation of the performance estimates obtained for experiment 1 are compared to the results evaluated earlier in Section 4.3.5 for the significant metric set. A positive change in error mean and standard deviation indicates that the experiment 1 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.5: Comparative evaluation of the significant metric set and experiment 1 estimates for the food chopper

	Accuracy			Precision		
	Significant Absolute Percentage Error Mean (%)	**Experiment 1 Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Experiment 1 Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	17.68	39.25	**-21.57**	58.74	45.46	**13.28**
FS-MV	3.22	13.40	**-10.18**	91.17	105.9	**-14.73**

The comparative evaluation suggests that experiment 1 predicts with lower accuracy in the case of both the FS-AT and FS-MV prediction models. The predictive precision is higher for experiment 1 when compared to the significant metric set for the FS-AT model but lower in the case of the FS-MV model.

5.3 Summary of the results of Experiment 1

This section evaluates the effect of manipulation of the significant complexity metrics in experiment 1 on the predictive accuracy and precision of the prediction models. In order to evaluate this effect, the changes in the accuracy and precision of the experiment 1 performance estimates from the significant metric set performance estimates are assessed. A positive change in accuracy and precision indicates that the set of complexity metrics used in experiment 1 predict better than the significant metric set. On the other hand, a negative change indicates that the significant metric set predicts better than experiment 1 metric set. Considering that the overall range of these change values across the four prediction models is large, the values falling within a range of ±15% from each other are considered to be equivalent to each other. Hence, only those changes in accuracy and precision which are beyond the ±15% range are considered to be suggestive (noteworthy). On the basis of this condition, a recommendation on which metric set works better for each test product is provided in Table 5.6.

Table 5.6: Recommendations on the metric set type to be used for each test product

Test Product	FS-AT prediction model		FS-MV prediction model		Recommendation
	Change in Accuracy (%)	Change in Precision (%)	Change in Accuracy (%)	Change in Precision (%)	
Sander	**-10.74**	**-1.1**	**17.64**	**-10.55**	Experiment 1
Hair dryer	**-56.94**	**-99.46**	**-104.00**	**-68.70**	Significant
Lawn mower	**19.07**	**24.83**	**19.56**	**-13.62**	Experiment 1
Flashlight	**-237.94**	**-138.47**	**-75.00**	**-73.4**	Significant
Food chopper	**-21.57**	**13.28**	**-10.18**	**-14.73**	Significant
Legend					
Experiment 1 predicts better (Change > 15%)			**Experiment 1 predicts worse (Change < -15%)**		

The sole considerable change observed for the test product sander, when the experiment 1 metric set is used, is the increase in predictive accuracy. Therefore, it is recommended to use the experiment 1 metric set for predicting the performance values of the sander. For the hair dryer and flashlight, the predictive accuracy and precision are seen to reduce considerably (Change < -15%) when the experiment 1 metric set is used. This is observed in the case of both the FS-AT and FS-MV prediction models. Hence, it is recommended to use the significant metric set for prediction for these two products. For the lawn mower, the experiment 1 metric set is recommended since it improves the overall predictive accuracy and precision. The only considerable change observed for the food chopper when the experiment 1 metric set is used is the reduction in accuracy. This is the reason why the significant metric set is recommended for the food chopper. On the whole, it is seen that the significant metric set works better for three test products (hair dryer, flashlight, food chopper) while the experiment 1 metric set works better for the other two products (sander and lawn mower).

5.4 Experiment 2: Intersection of FS-AT and FS-MV significant metric sets

The complexity metric vector for this experiment includes the significant metrics that are common amongst the FS-AT and FS-MV models. This complexity vector is then used to train and test the ANNs for the same set of consumer products as for the previous analyses.

5.4.1 Test product: Sander

Figure 5.6 illustrates histogram plots for the sander corresponding to the FS-AT and FS-MV prediction models. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

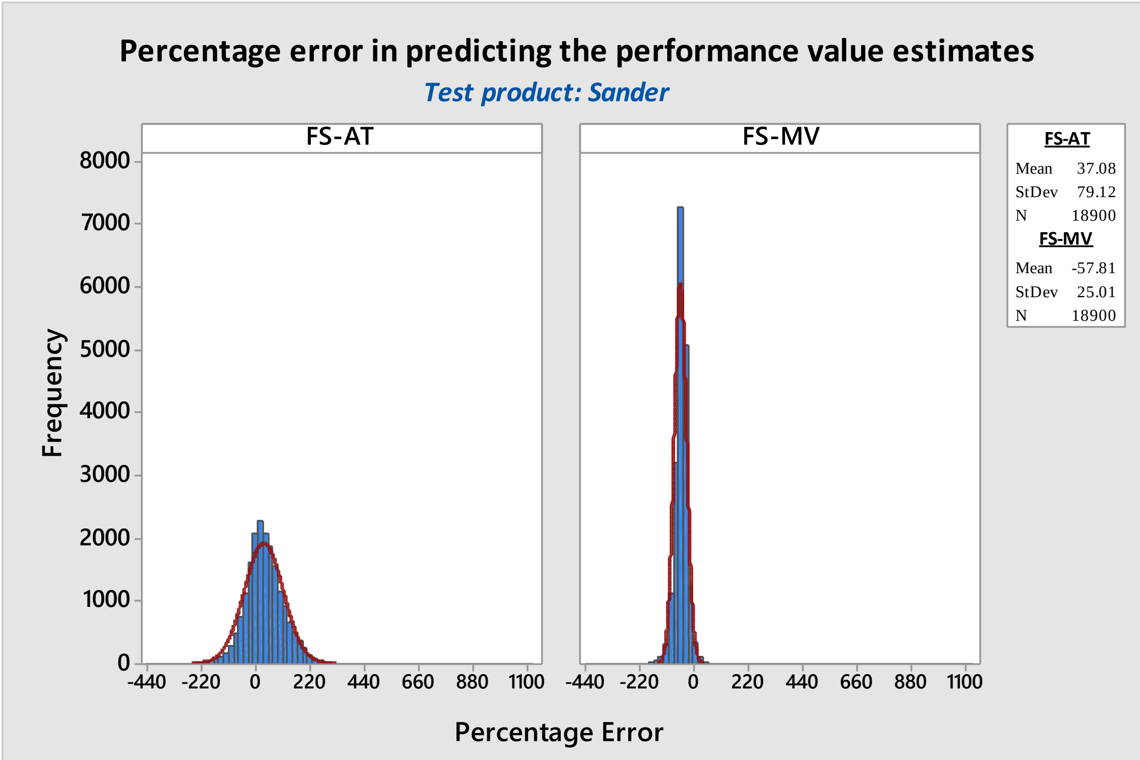


Figure 5.6: Percentage error in prediction for the sander for experiment 2

The FS-AT prediction model is more accurate with an absolute percentage error mean of 37.08% as compared to the FS-MV model which has an absolute percentage error mean of 57.81%. However, the FS-MV model performs better than the FS-AT model in terms of precision with a percentage error standard deviation of 25.01% against the FS-AT model's 79.12%. In Table 5.7, the percentage error mean and standard deviation of the performance estimates obtained for experiment 2 are compared to the results evaluated earlier in Section 4.3.1 for the significant metric set. A positive change in error mean and standard deviation indicates that the experiment 1 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.7: Comparative evaluation of the significant metric set and experiment 2 estimates for the sander

	Accuracy			Precision		
	Significant Absolute Percentage Error Mean (%)	**Experiment 2 Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Experiment 2 Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	40.40	37.08	**3.32**	88.51	79.12	**9.39**
FS-MV	72.02	57.81	**14.21**	20.68	25.01	**-4.33**

The comparative evaluation suggests that experiment 2 predicts with higher accuracy in the case of both FS-AT and FS-MV prediction models. The predictive precision is lower for experiment 2 when compared to the significant metric set for the FS-MV model.

5.4.2 Test product: Hair dryer

Figure 5.7 illustrates histogram plots for the hair dryer corresponding to the FS-AT and FS-MV prediction models. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

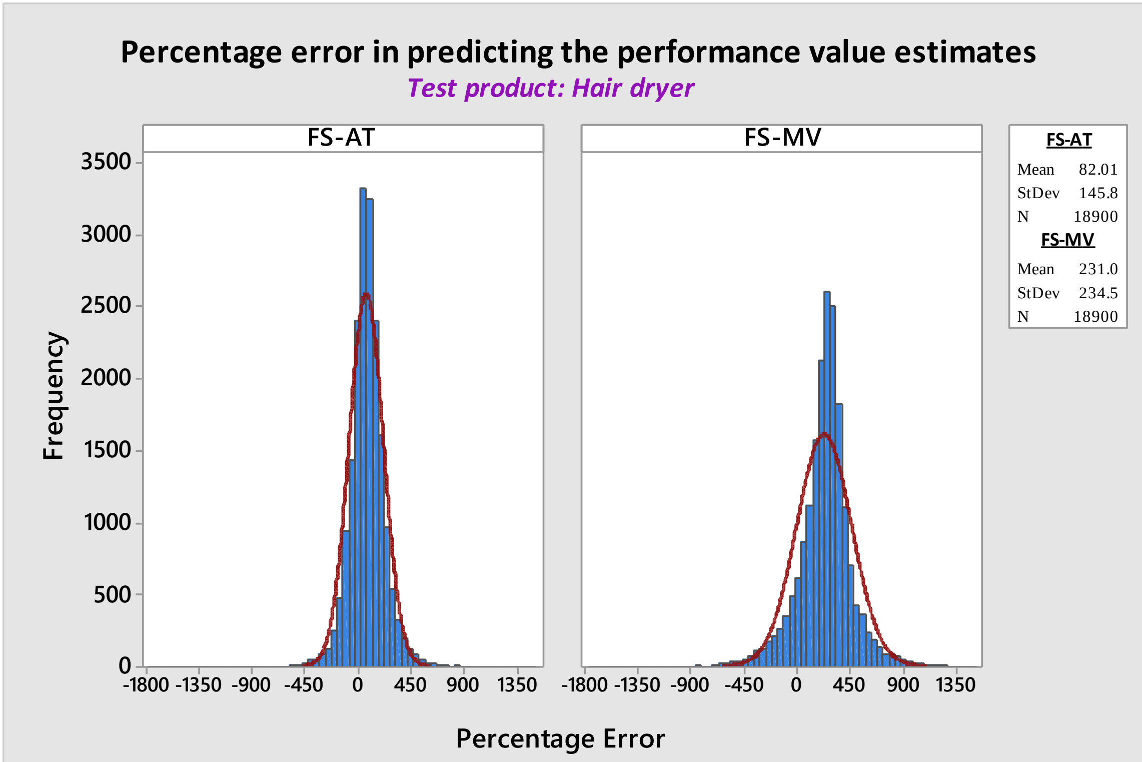


Figure 5.7: Percentage error in prediction for the hair dryer for experiment 2

The FS-AT prediction model is more accurate with an absolute percentage error mean of 82.01% as compared to the FS-MV model which has an absolute percentage error mean of 231.00%. The FS-AT model performs better than the FS-MV model in terms of precision as well with a percentage error standard deviation of 145.8% against the FS-MV model's standard deviation of 234.5%. In Table 5.8, the percentage error mean and standard deviation of the performance estimates obtained for experiment 2 are compared to the results evaluated earlier in Section 4.3.2 for the significant metric set. A positive change in error mean and standard deviation indicates that the experiment 2 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.8: Comparative evaluation of the significant metric set and experiment 2 estimates for the hair dryer

	Accuracy			**Precision**		
	Significant Absolute Percentage Error Mean (%)	**Experiment 2 Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Experiment 2 Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	24.91	82.01	**-57.1**	65.84	145.8	**-79.96**
FS-MV	127.6	231.00	**-103.4**	193.2	234.5	**-41.3**

The comparative evaluation suggests that experiment 2 predicts with lower accuracy and precision in the case of both FS-AT and FS-MV prediction models. This suggests that for the hair dryer, the predictive accuracy and precision is better when the respective sets of significant metrics identified for the two models are used for prediction.

5.4.3 Test product: Lawn mower

Figure 5.8 illustrates histogram plots for the lawn mower corresponding to the FS-AT and FS-MV prediction models. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

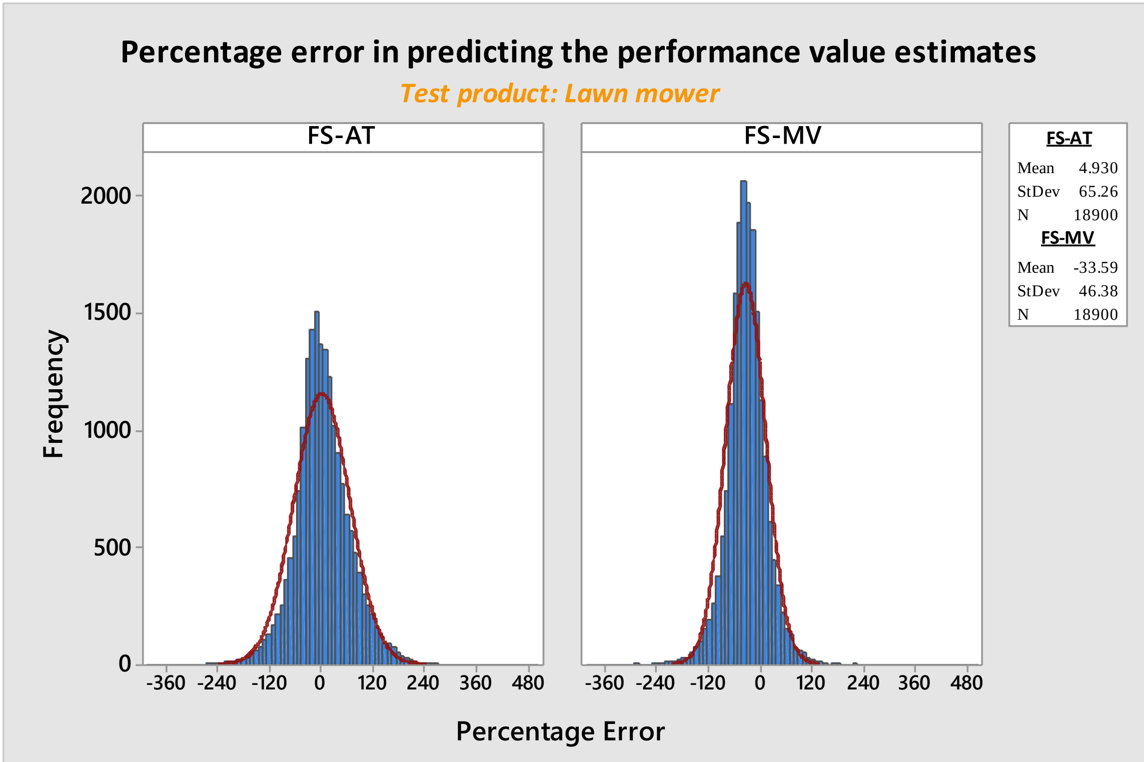


Figure 5.8: Percentage error in prediction for the lawn mower for experiment 2

The FS-AT prediction model is more accurate with an absolute percentage error mean of 4.93% as compared to the FS-MV model which has an absolute percentage error mean of 33.59%. However, the FS-MV model performs better than the FS-AT model in terms of precision with a percentage error standard deviation of 46.38% against the FS-AT model's 65.26%. In Table 5.9, the percentage error mean and standard deviation of the performance estimates obtained for experiment 2 are compared to the results evaluated earlier in Section 4.3.3 for the significant metric set. A positive change in error mean and standard deviation indicates that the experiment 1 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.9: Comparative evaluation of the significant metric set and experiment 2 estimates for the lawn mower

	Accuracy			Precision		
	Significant Absolute Percentage Error Mean (%)	**Experiment 2 Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Experiment 2 Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	29.35	4.93	**24.42**	93.59	65.26	**28.33**
FS-MV	43.53	33.59	**9.94**	44.38	46.38	**-2.00**

The comparative evaluation suggests that experiment 1 predicts with higher accuracy in the case of both FS-AT and FS-MV prediction models. The predictive precision is lower for experiment 2 when compared to the significant metric set for the FS-MV model.

5.4.4 Test product: Flashlight

Figure 5.9 illustrates histogram plots for the flashlight corresponding to the FS-AT and FS-MV prediction models. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

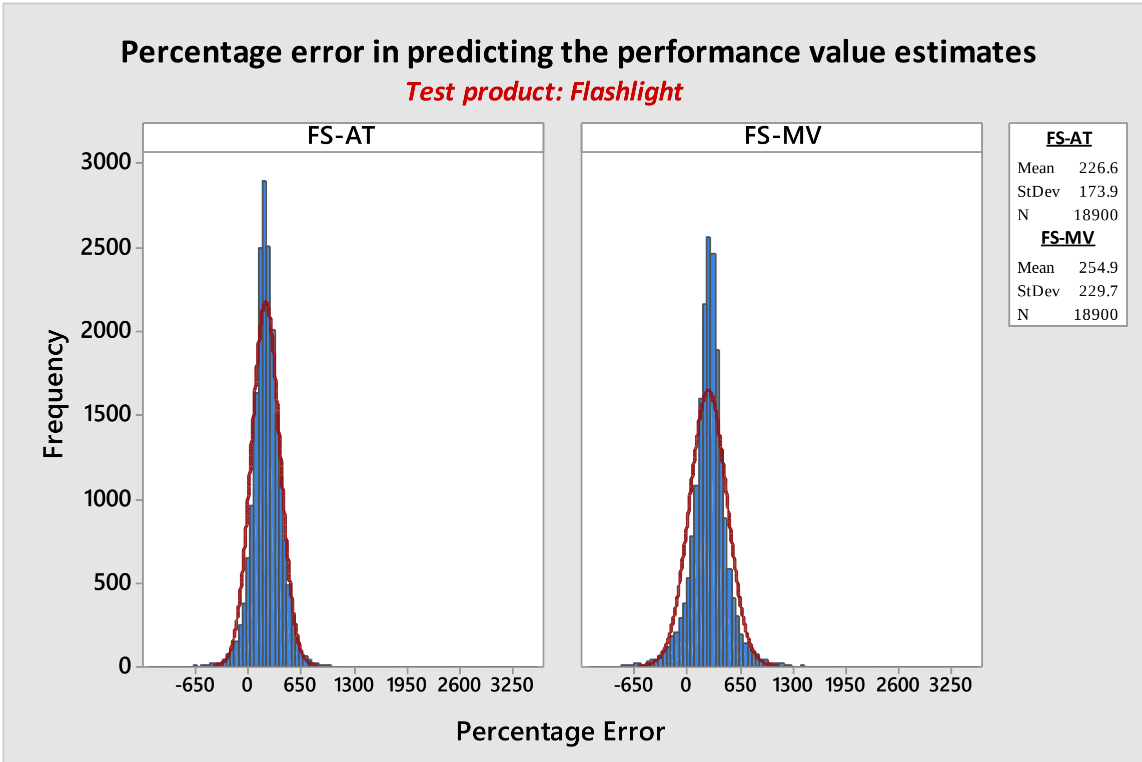


Figure 5.9: Percentage error in prediction for the flashlight for experiment 2

The FS-AT prediction model is more accurate with an absolute percentage error mean of 226.6% as compared to the FS-MV model which has an absolute percentage error mean of 254.9%. The FS-AT model performs better than the FS-MV model in terms of precision as well with a percentage error standard deviation of 173.9% against the FS-MV model's standard deviation of 229.7%. In Table 5.10, the percentage error mean and standard deviation of the performance estimates obtained for experiment 2 are compared to the results evaluated earlier in Section 4.3.4 for the significant metric set. A positive change in error mean and standard deviation indicates that the experiment 2 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.10: Comparative evaluation of the significant metric set and experiment 2 estimates for the flashlight

	Accuracy			Precision		
	Significant Absolute Percentage Error Mean (%)	**Experiment 2 Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Experiment 2 Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	9.06	226.6	**-217.54**	64.33	173.9	**-109.57**
FS-MV	210.7	254.9	**-44.2**	220.1	229.7	**-9.6**

The comparative evaluation suggests that experiment 2 predicts with lower accuracy and precision in the case of both the FS-AT and FS-MV prediction models. This suggests that for the flashlight, the predictive accuracy and precision is better when the respective sets of significant metrics identified for the two models are used for prediction.

5.4.5 Test product: Food chopper

Figure 5.10 illustrates histogram plots for the food chopper corresponding to the FS-AT and FS-MV prediction models. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

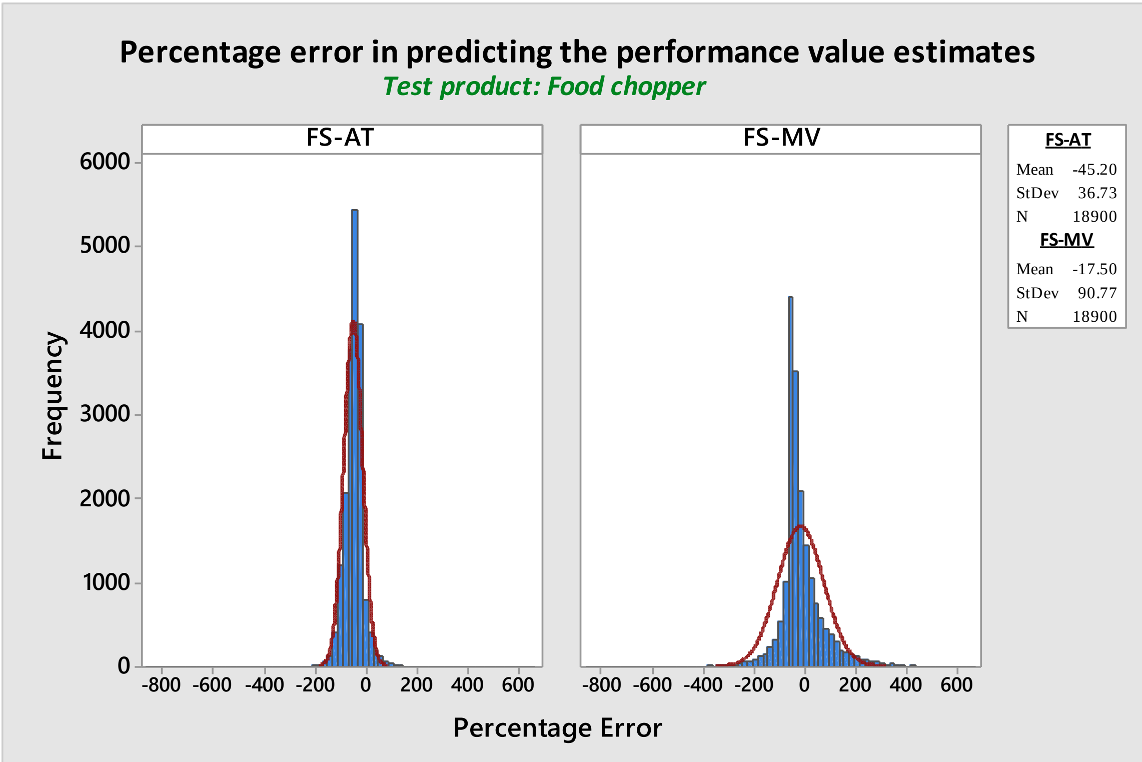


Figure 5.10: Percentage error in prediction for the food chopper for experiment 2

For the food chopper, the FS-MV prediction model is more accurate with an absolute percentage error mean of 17.50% as compared to the FS-AT model which has an absolute percentage error mean of 45.20%. However, the FS-AT model performs better than the FS-MV model in terms of precision with a percentage error standard deviation of 36.73% against the FS-MV model's standard deviation of 90.77%. In Table 5.11, the percentage error mean and standard deviation of the performance estimates obtained for experiment 2 are compared to the results evaluated earlier in Section 4.3.5 for the significant metric set. A positive change in error mean and standard deviation indicates that the experiment 2 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.11: Comparative evaluation of the significant metric set and experiment 2 estimates for the food chopper

	Accuracy			Precision		
	Significant Absolute Percentage Error Mean (%)	**Experiment 2 Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Experiment 2 Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	17.68	45.20	**-27.52**	58.74	36.73	**22.01**
FS-MV	3.22	17.50	**-14.28**	91.17	90.77	**0.4**

The comparative evaluation suggests that experiment 2 predicts with lower accuracy in the case of both the FS-AT and FS-MV prediction models. The predictive precision is higher for experiment 2 when compared to the significant metric set for both the FS-AT and FS-MV models.

5.5 Summary of the results of Experiment 2

This section evaluates the effect of manipulation of the significant complexity metrics in experiment 2 on the predictive accuracy and precision of the prediction models. In order to evaluate this effect, the changes in the accuracy and precision of the experiment 2 performance estimates from the significant metric set performance estimates are assessed. A positive change in accuracy and precision indicates that the set of complexity metrics used in experiment 2 predict better than the significant metric set. On the other hand, a negative change indicates that the significant metric set predicts better than experiment 2. Considering that the overall range of these change values across the four prediction models is large, the values falling within a range of ±15% from each other are considered to be equivalent to each other. Hence, only those changes in accuracy and precision which are beyond the ±15% range are considered to be suggestive. On the basis of this condition, a recommendation on which metric set works better for each test product is provided in Table 5.12.

Table 5.12: Recommendations on the metric set type to be used for each test product

Test Product	FS-AT prediction model: Change in Accuracy (%)	FS-AT prediction model: Change in Precision (%)	FS-MV prediction model: Change in Accuracy (%)	FS-MV prediction model: Change in Precision (%)	Recommendation
Sander	3.32	9.39	14.21	-4.33	Either
Hair dryer	-57.1	-79.96	-103.4	-41.30	Significant
Lawn mower	24.42	28.33	9.94	-2.00	Experiment 2
Flashlight	-217.54	-109.57	-44.2	-9.6	Significant
Food chopper	-27.52	22.01	-14.28	0.4	Inconclusive

Legend	
Experiment 2 predicts better (Change > 15%)	Experiment 2 predicts worse (Change < -15%)

The test results for the sander suggest that there are no considerable changes observed in either predictive accuracy or precision in the case of both the FS-AT and FS-MV prediction models. Therefore, it is recommended to use the experiment 2 metric set for predicting the performance values of the sander. For the hair dryer and flashlight, the predictive accuracy and precision are seen to reduce considerably when the experiment 2 metric set is used. This is observed in the case of both the FS-AT and FS-MV prediction models. Hence, it is recommended to use the significant metric set for prediction for these two products. For the lawn mower, the experiment 2 metric set is recommended since it is seen to improve the predictive accuracy and precision for the FS-AT prediction model whereas no considerable changes are observed for the FS-MV prediction model. The test results for the food chopper are inconclusive to make a recommendation on the metric set to be used for prediction, since there are equal number of positive and negative changes in predictive accuracy and precision. On the whole, it is seen that the significant metric set works better for two test products (hair dryer and flashlight) while the experiment 2 metric set works better for one product (lawn mower). Either of the two metric sets can be used for the test product sander.

5.6 Experiment 3: Union of all the significant metrics

Experiment 3 is conducted for a comprehensive set involving the union of all the significant metrics across each of the four prediction models. This complexity vector is then used to train and test the ANNs for the same set of consumer products as for the previous analyses.

5.6.1 Test product: Sander

Figure 5.11 illustrates histogram plots for the sander corresponding to the four models, depicting frequency distribution of the percentage errors in prediction. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

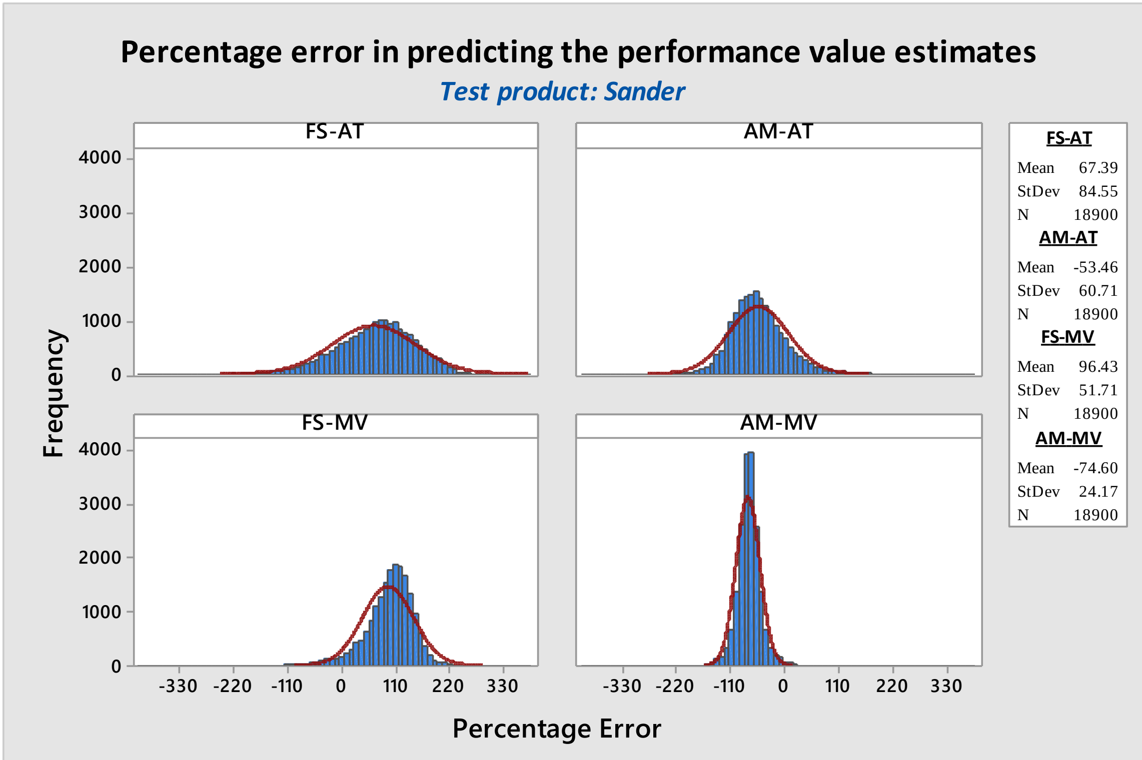


Figure 5.11: Percentage error in prediction for the sander for experiment 3

The plots suggest that the FS-MV and AM-MV prediction models are more precise but less accurate as compared to the FS-AT and AM-AT models for the Sander. These test results are further compared to the test results obtained using the significant set of complexity metrics in Table 5.13. A positive change in error mean and standard deviation indicates that the experiment 3 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.13: Comparative evaluation of the significant metric set and experiment 3 estimates for the sander

	Accuracy			Precision		
	Significant Absolute Percentage	Experiment 3 Absolute Percentage	Change in Error Mean	Significant Absolute Percentage	Experiment 3 Absolute Percentage	Change in Error Standard

	Error Mean (%)	Error Mean (%)	(%)	Error Standard deviation (%)	Error Standard deviation (%)	deviation (%)
FS-AT	40.40	67.39	**-26.99**	88.51	84.55	**3.96**
AM-AT	38.26	53.46	**-15.2**	66.85	60.71	**6.14**
FS-MV	72.02	96.43	**-24.41**	20.68	51.71	**-31.03**
AM-MV	71.96	74.60	**-2.64**	16.47	24.17	**-7.7**

The comparative evaluation for the test product sander suggests that Experiment 3 predicts with lower accuracy for each of the four prediction models. The predictive precision is seen to increase for the FS-AT and AM-AT prediction models and decrease for the FS-MV and AM-MV prediction models when the Experiment 3 union metric set is used.

5.6.2 Test product: Hair dryer

Figure 5.12 illustrates histogram plots for the hair dryer corresponding to the four models, depicting frequency distribution of the percentage errors in prediction. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

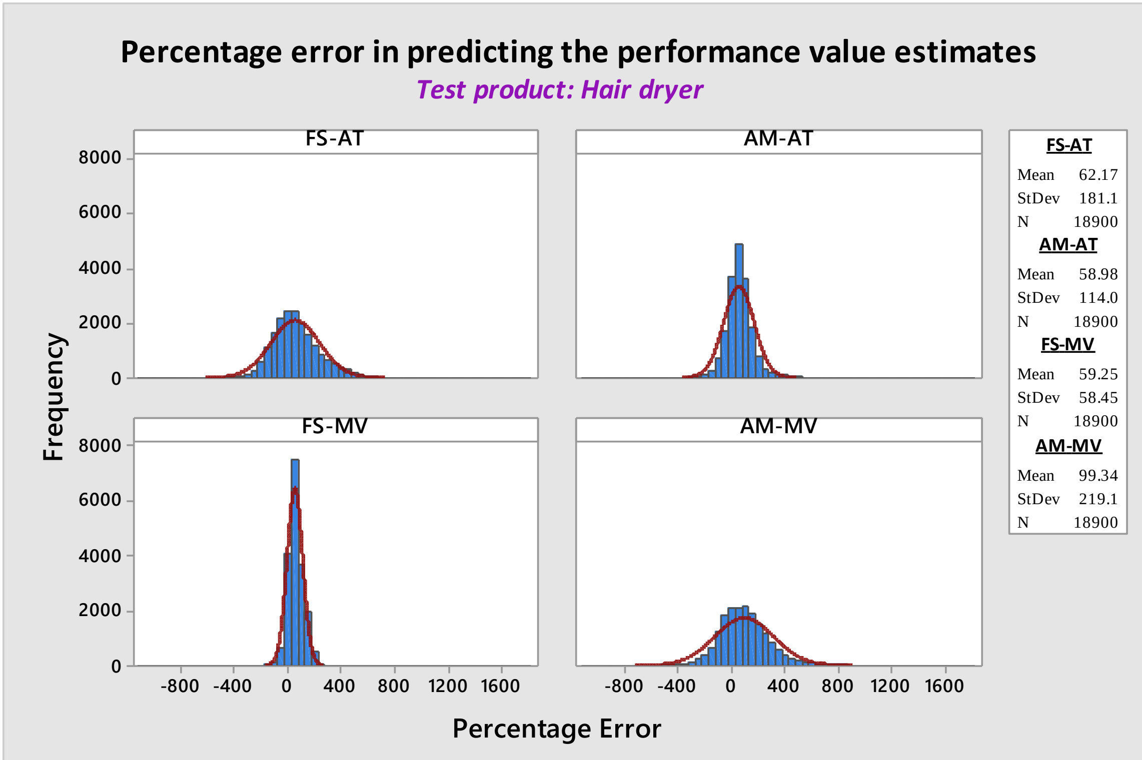


Figure 5.12: Percentage error in prediction for the hair dryer for experiment 3

The histograms suggest that the AM-AT prediction model is the most accurate with an absolute percentage error mean of 58.98% whereas the FS-MV prediction model is the most precise with an absolute percentage error standard deviation of 58.45%. The AM-MV model is the least accurate and precise with absolute percentage error mean and standard deviation of 99.34% and 219.1% respectively. These test results are further compared to the test results obtained using the significant metric set of complexity metrics in Table 5.14. A positive change in error mean and standard deviation indicates that the experiment 3 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.14: Comparative evaluation of the significant metric set and experiment 3 estimates for the hair dryer

	Accuracy			Precision		
	Significant Absolute Percentage Error Mean (%)	**Experiment 3 Absolute Percentage Error Mean (%)**	**Change in Error Mean (%)**	**Significant Absolute Percentage Error Standard deviation (%)**	**Experiment 3 Absolute Percentage Error Standard deviation (%)**	**Change in Error Standard deviation (%)**
FS-AT	24.91	62.17	**-37.26**	65.84	181.1	**-115.26**
AM-AT	32.50	58.98	**-26.48**	133.8	114.0	**19.8**
FS-MV	127.6	59.25	**68.35**	193.2	58.45	**134.75**
AM-MV	28.11	99.34	**-71.23**	172.4	219.1	**-46.7**

The comparative evaluation for the test product hair dryer suggests that using the Experiment 3 metric set for prediction improves predictive accuracy only for the FS-MV prediction model. The predictive precision is seen to improve for the AM-AT and FS-MV prediction models when the Experiment 3 metric set is used.

5.6.3 Test product: Lawn mower

Figure 5.13 illustrates histogram plots for the lawn mower corresponding to the four models, depicting frequency distribution of the percentage errors in prediction. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

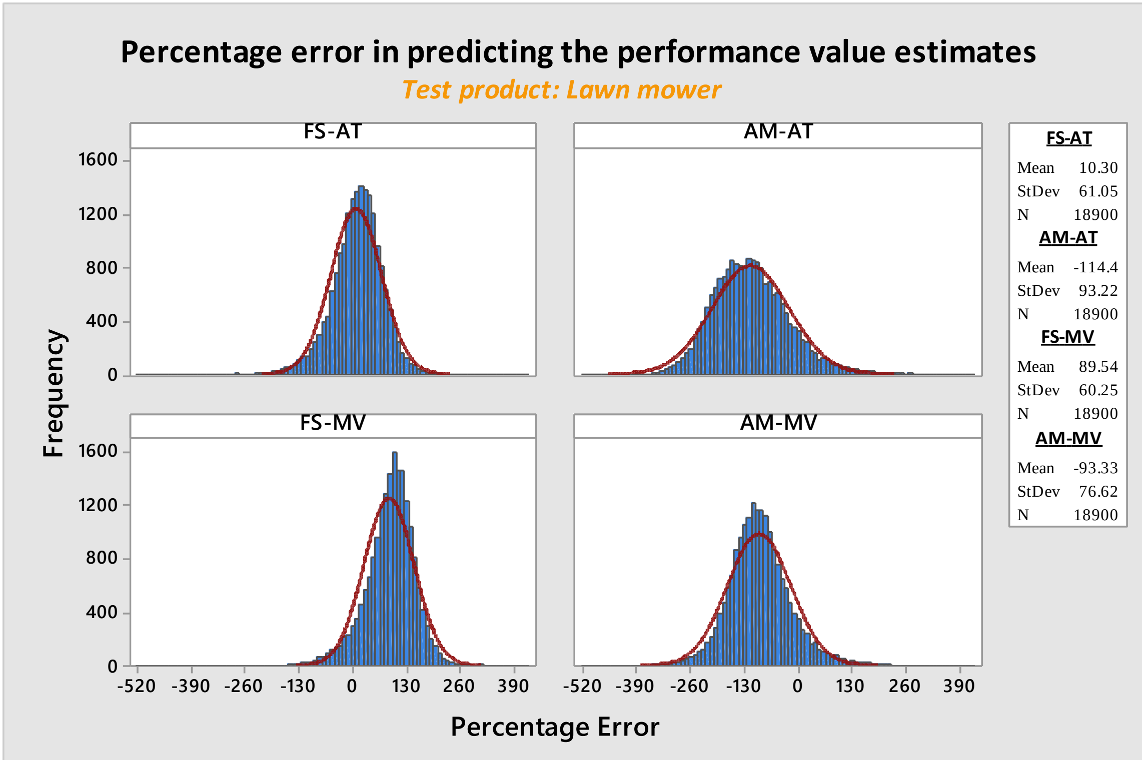


Figure 5.13: Percentage error in prediction for the lawn mower for experiment 3

The histograms suggest that the FS-AT prediction model is the most accurate with an absolute percentage error mean of 10.30% whereas the FS-MV prediction model is the most precise with an absolute percentage error standard deviation of 60.25%. These test results are further compared to the test results obtained using the significant metric set of complexity metrics in Table 5.15. A positive change in error mean and standard deviation indicates that the experiment 3 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.15: Comparative evaluation of the significant metric set and experiment 3 estimates for the lawn mower

	Accuracy			Precision		
	Significant	Experiment	Change	Significant	Experiment	Change in

	Absolute Percentage Error Mean (%)	3 Absolute Percentage Error Mean (%)	in Error Mean (%)	Absolute Percentage Error Standard deviation (%)	3 Absolute Percentage Error Standard deviation (%)	Error Standard deviation (%)
FS-AT	29.35	10.30	**19.05**	93.59	61.05	**32.54**
AM-AT	32.16	-114.40	**146.56**	54.85	93.22	**-38.37**
FS-MV	43.53	89.54	**-46.01**	44.38	60.25	**-15.87**
AM-MV	58.26	-93.33	**151.59**	35.21	76.62	**-41.41**

The comparative evaluation for the test product lawn mower suggests that using the Experiment 3 metric set for prediction improves predictive accuracy for the FS-AT, AM-AT, and AM-MV prediction models. The predictive precision is seen to improve only for the FS-AT prediction model when the Experiment 3 metric set is used.

5.6.4 Test product: Flashlight

Figure 5.14 illustrates histogram plots for the flashlight corresponding to the four models, depicting frequency distribution of the percentage errors in prediction. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

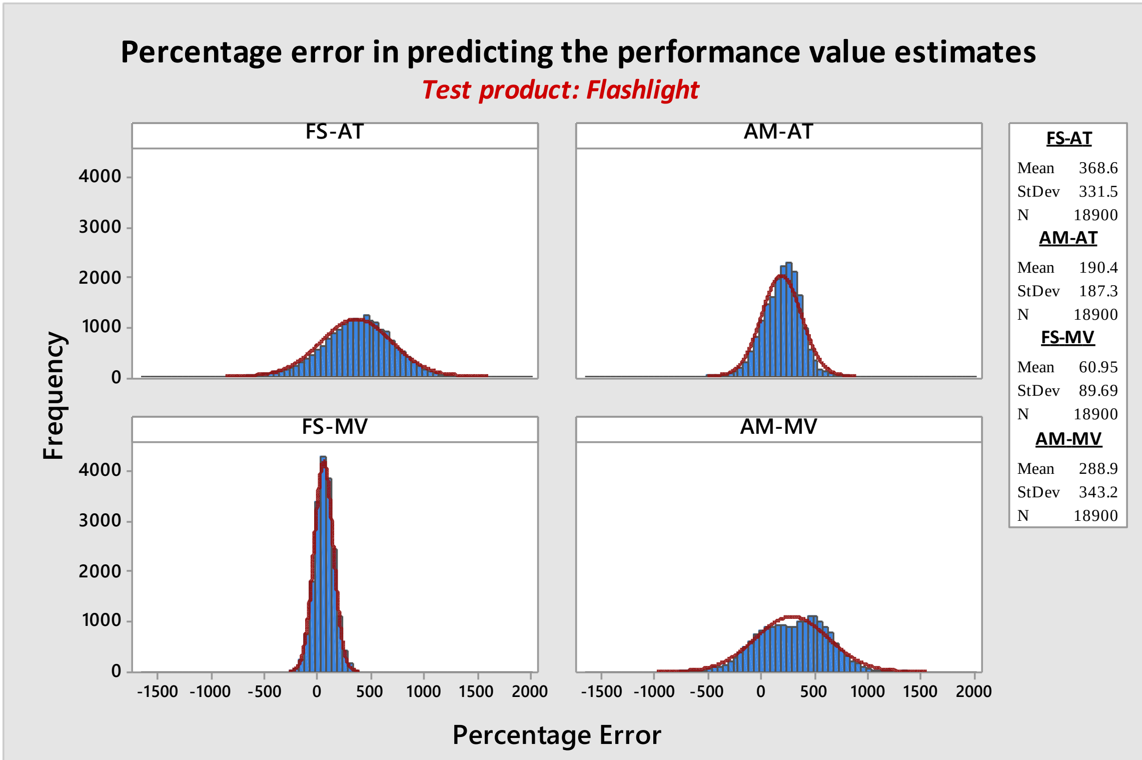


Figure 5.14: Percentage error in prediction for the flashlight for experiment 3

The histograms suggest that the FS-MV prediction model is both the most accurate and precise with absolute percentage error mean and standard deviation of 60.95% and 89.69% respectively. These test results are further compared to the test results obtained using the significant metric set of complexity metrics in Table 5.16. A positive change in error mean and standard deviation indicates that the experiment 3 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.16: Comparative evaluation of the significant metric set and experiment 3 estimates for the flashlight

	Accuracy			Precision		
	Significant	**Experiment**	**Change**	**Significant**	**Experiment**	**Change in**

	Absolute Percentage Error Mean (%)	3 Absolute Percentage Error Mean (%)	in Error Mean (%)	Absolute Percentage Error Standard deviation (%)	3 Absolute Percentage Error Standard deviation (%)	Error Standard deviation (%)
FS-AT	9.06	368.6	**-359.54**	64.33	331.5	**-267.17**
AM-AT	140.1	190.4	**-50.3**	186.1	187.3	**-1.2**
FS-MV	210.7	60.95	**149.75**	220.1	89.69	**130.41**
AM-MV	0.94	288.9	**-287.96**	242.1	343.2	**-101.1**

The comparative evaluation for the test product flashlight suggests that using the Experiment 3 metric set for prediction improves predictive accuracy and precision only for the FS-MV prediction model.

5.6.5 Test product: Food chopper

Figure 5.15 illustrates histogram plots for the food chopper corresponding to the four models, depicting frequency distribution of the percentage errors in prediction. The X-axis represents the percentage error in predicting the performance value estimates and the Y-axis represents the frequency of the percentage errors.

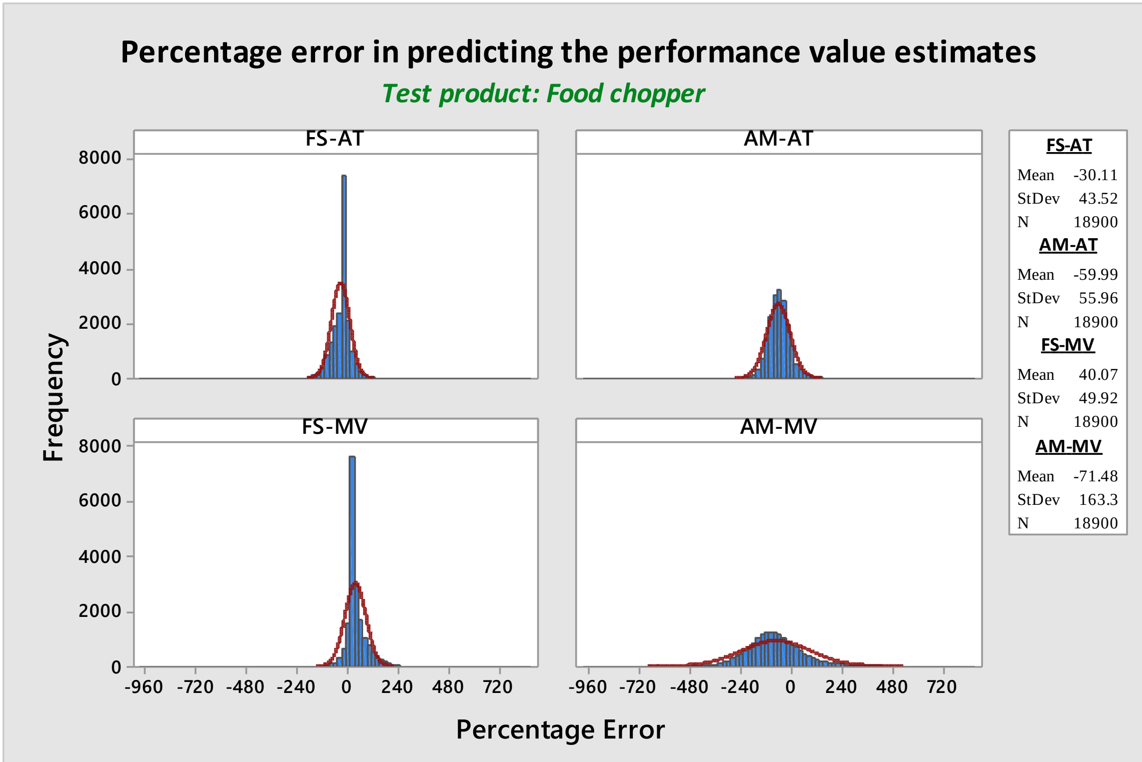


Figure 5.15: Percentage error in prediction for the food chopper for experiment 3

The histograms suggest that the FS-AT prediction model is both the most accurate and precise with absolute percentage error mean and standard deviation of 30.11% and 43.52% respectively. These test results are further compared to the test results obtained using the significant metric set of complexity metrics in Table 5.17. A positive change in error mean and standard deviation indicates that the experiment 3 metrics predict with higher accuracy and precision respectively as compared to the significant metric set and vice versa.

Table 5.17: Comparative evaluation of the significant metric set and experiment 3 estimates for the food chopper

	Accuracy			Precision		
	Significant	Experiment	Change	Significant	Experiment	Change in

	Absolute Percentage Error Mean (%)	3 Absolute Percentage Error Mean (%)	in Error Mean (%)	Absolute Percentage Error Standard deviation (%)	3 Absolute Percentage Error Standard deviation (%)	Error Standard deviation (%)
FS-AT	17.68	30.11	**-12.43**	58.74	43.52	**15.22**
AM-AT	32.54	59.99	**-27.45**	53.86	55.96	**-2.1**
FS-MV	3.22	40.07	**-36.85**	91.17	49.92	**41.25**
AM-MV	34.45	-71.48	**105.93**	95.25	163.3	**-68.05**

The comparative evaluation for the test product food chopper suggests that using the Experiment 3 metric set for prediction improves predictive accuracy only for the AM-MV prediction model. In the case of precision, the FS-AT and FS-MV prediction models predict better when the experiment 3 metric set is used.

5.7 Summary of the results of Experiment 3

This section evaluates the effect of manipulation of the significant complexity metrics in experiment 3 on the predictive accuracy and precision of the prediction models. In order to evaluate this effect, the changes in the accuracy and precision of the experiment 3 performance estimates from the significant metric set performance estimates are assessed. A positive change in accuracy and precision indicates that the set of complexity metrics used in experiment 3 predict better than the significant metric set. On the other hand, a negative change indicates that the significant metric set predicts better than experiment 3. Considering that the overall range of these change values across the four prediction models is large, the values falling within a range of ±15% from each other are considered to be equivalent to each other. Hence, only those changes in accuracy and precision which are beyond the ±15% range are considered to be suggestive. On the basis of this condition, a recommendation on which metric set works better for each test product is provided in Table 5.18.

Table 5.18: Recommendations on the metric set type to be used for each test product

Test Product	Change in Accuracy (%)				Change in Precision (%)				Recommendation
	FS-AT	AM-AT	FS-MV	AM-MV	FS-AT	AM-AT	FS-MV	AM-MV	
Sander	**-26.99**	**-15.20**	**-24.41**	**-2.64**	**3.96**	**6.14**	**-31.03**	**-7.70**	Significant
Hair dryer	**-37.26**	**-26.48**	**68.35**	**-71.23**	**-115.2**	**19.80**	**134.75**	**-46.70**	Significant
Lawn mower	**19.05**	**146.56**	**-46.01**	**151.59**	**32.54**	**-38.3**	**-15.87**	**-41.41**	Inconclusive
Flash-light	**-359.5**	**-50.30**	**149.75**	**-287.9**	**-267.1**	**-1.20**	**130.41**	**-101.1**	Significant
Food chopper	**-12.43**	**-27.45**	**-36.85**	**105.93**	**15.22**	**-2.10**	**41.25**	**-68.25**	Inconclusive
Legend									
Experiment 3 predicts better (Change > 15%)					**Experiment 3 predicts worse (Change < -15%)**				

The predictive accuracy and precision is seen to reduce considerably for the test product sander when the experiment 3 metric set is used across the four prediction models. Thus, the significant metric set is recommended for predicting the performance values of the sander. For the hair dryer and flashlight, there is both a decrease and increase in the predictive accuracy and precision when the experiment 3 metric set is used. On the whole, there is a negative change (decrease) in predictive accuracy and precision in 5 out of 8 cases. Hence, it is recommended to use the significant metric set for the hair dryer and flashlight. The test results for the lawn mower and food chopper are inconclusive to make a recommendation on the metric set to be used for prediction, since there are equal number of positive and negative changes in predictive accuracy and precision.

Thus, it is seen that experiment 3, which contains the union of all the significant metrics from the four prediction models, does not improve predictive accuracy and precision when compared to the significant metric sets. The significant metric sets perform better in prediction because each set comprises of complexity metrics that are influential for the specific prediction model.

Chapter Six
CONCLUSIONS AND FUTURE WORK

This chapter presents an overview of the research conducted in this thesis and its potential extensions in the future. The thesis focused on analyzing the precision of the design representations (assembly models and function structures) and understanding complexity as an enabler in predicting the performance value estimates (assembly time and market value). The three research questions identified earlier in Chapter Two were addressed through this thesis.

6.1 Answers to Research Question 1

Chapter Three addressed Research Question 1 through the precision analysis of the design representations (assembly models and function structures) in predicting the performance values of the products (assembly time and market value). Research Question 1 is as follows:

> *How does precision vary with the design representations (assembly models and function structures) and performance values of the products (assembly time and market value)?*

A precision rank order was determined for each of the four surrogate prediction models on the basis of the absolute percentage error standard deviation (predictive precision) of the performance value estimates. Further, a comparative evaluation of the predictive accuracy [8] and precision rank orders of the four prediction models was conducted; in order to assess the predictive performance of the design representations in estimating the performance values. The Assembly Model - Assembly Time (AM-AT) prediction model was ranked 1 for both predictive accuracy and precision; indicating that given assembly models, one can consistently predict accurate assembly times. The Function Structure - Assembly Time prediction model was ranked 3 for accuracy and 2 for its precision whereas the Function Structure - Market Value prediction model ranked 4 for its accuracy and 3 for precision. The Assembly Model - Market Value (AM-MV) prediction model was ranked 2 for its predictive accuracy but ranked 4 for its precision which demonstrates that it is accurate in predicting the performance values but not with enough consistency. This lack of precision could be due to the fact that the assembly models do not contain information regarding all the factors that contribute towards a product's market value. For instance, information such as product material, labor cost, manufacturing cost etc. which factor in a product's market value are not contained in assembly models.

6.2 Answers to Research Question 2

The sensitivity analysis conducted in Chapter Four focused on addressing Research Question 2, which is as follows:

> *Which are the most influential complexity metrics in predicting the performance values of the products?*

The results of the analysis suggested that for each design representation, there exists a set of complexity metrics that are influential (significant) predictors of performance values. There exists at least one metric from each class (size, interconnection, centrality, and decomposition) which is identified as a significant predictor. Two out of the twenty nine complexity metrics are found to be significant for all the four surrogate prediction models; m1: the number of elements and m25: the density of the in-core numbers. An observation of interest is that more number of centrality metrics are found to be significant for the assembly model design representation as compared to the function structures. This can be explained by the fact that the product dataset analyzed comprises of consumer products that are generally designed to be highly modular for ease of manufacturing and assembly. This modularity (or centrality) is not as evident in the function structures.

The complexity metrics identified as significant predictors for the corresponding four prediction models were further used to train and test the ANNs instead of the original set of twenty nine complexity metrics. The test results suggested that on the whole the precision of the prediction models increases but the predictive accuracy decreases when the significant metric set is used for prediction. In spite of their relatively low prediction accuracy, these significant complexity metrics can still prove to be valuable predictors of later stage information considering the fact that they are evaluated using early design stage representations. It is important to note that in the early design stage, the product structural information available is minimal. Hence, these early design stage significant metrics with relatively low accuracy can be as valuable as the metrics evaluated using a more detailed design representation with higher accuracy in predicting the same information. These significant metrics will enable designers to consider the impacts of their decisions in the early design stage using exact quantifiers rather than subjective judgments. This can eventually lead to cost savings by making more informed decisions earlier in the design process.

6.3 Answers to Research Question 3

The objective behind the experiments conducted in Chapter Five was to investigate the effect of manipulation of the significant complexity metrics and in turn answer Research Question 3. This research question is:

> *How will manipulation of the significant complexity metric inputs identified for each prediction model affect the performance value prediction of the products?*

The experiment 1 test results suggest that the significant metric set works better in predicting the performance values for three test products (hair dryer, flashlight, food chopper) while the experiment 1 metric set works better for the other two products (sander and lawn mower). The test results obtained from experiment 2 indicate that the significant metric set works better for three test products (hair dryer, flashlight, food chopper) while experiment 2 metric set works better for one product (lawn mower). Either of the two metric sets can be used for the test product sander. The performance value estimates evaluated using the Experiment 3 metric set demonstrate that in most cases this metric set does not improve predictive accuracy and precision when compared to the significant metric sets.

On the whole, it is observed that the unique significant metric sets perform better in predicting the product performance values as compared to the manipulated metric sets in experiments 1 through 3. This suggests that the unique significant metric sets identified specifically for each prediction model work best when used for predicting the performance value estimates of the corresponding model.

6.4 Future Work

In this thesis, the complexity metrics identified as influential (significant) predictors demonstrated the ability to improve the predictive precision of the performance value estimates; when used to train and test the artificial neural networks (ANNs). However, the use of these significant complexity metrics resulted in a decrease in the predictive accuracy of the performance value estimates. Further work needs to be conducted in an attempt to shift these precise measurements towards the target value. The current set of consumer products used for training and testing the ANNs vary widely in terms of architecture (structure). It is hypothesized that the predictive accuracy can be improved by training and testing the artificial neural networks using consumer products that have similar product architectures or those from within the same category of consumer products. For instance, exclusive use of products those fall under the category of consumer power tools. Previous research has indicated that the predictive accuracy increases when products from a specific company and within the same category are used to estimate assembly times, given assembly models [15]. The following research question summarizes the above mentioned future work:

> *How does the predictive accuracy of the significant metric set vary when products belonging to the same category are used for training and testing the artificial neural networks?*

Currently, the Graph Complexity Connectivity Method used in this thesis predicts the product performance values: assembly time and market value, given the design representations: assembly models and function structures. Future research efforts can seek to investigate how this method can be extended to predict other performance values such as product defects. This can be achieved by using previous assembly models and the corresponding product defect data to train the artificial neural networks. The trained artificial neural networks can then be used to predict potential defects in the new product assembly models. This will enable manufacturing of better quality products through product defect estimation early in the design stage.

> *How can the Graph Complexity Connectivity Method be extended to predict other performance values such as product defects using assembly models?*

REFERENCES

[1] Suh, N., 1999, “A theory of complexity, periodicity and the design axioms,” Research in Engineering Design.

[2] Pahl, G., Beitz, W., Wallace, K., and Council, D., 1984, Engineering design.

[3] Ullman, D., 1992, The mechanical design process.

[4] Ameri, F., Summers, J., Mocko, G., and Porter, M., 2008, “Engineering design complexity: an investigation of methods and measures,” Research in Engineering Design 19.2-3 (2008): 161-179.

[5] Caprace, J. D., and Rigo, P., 2012, “A real-time assessment of the ship design complexity,” CAD Computer Aided Design, **44**(3), pp. 203–208.

[6] Du, D., and Ko, K., 2011, Theory of computational complexity.

[7] Summers, J., and Shah, J., 2010, “Mechanical engineering design complexity metrics: size, coupling, and solvability,” Summers, J. D., & Shah, J. J. (2010). Mechanical engineering design complexity metrics: size, coupling, and solvability. Journal of Mechanical Design, 132(2), 021004.

[8] Vasala, C., and Mohinder, S., 2014, “A Comparative Study: Structural Complexity Metrics applied against Function and Assembly Product Graphs in Predicting Market Price and Assembly Time.”

[9] Owensby, E., 2012, “Representation: extracting mate complexity from assembly models to automatically predict assembly times,” ASME 2012 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. American Society of Mechanical Engineers, 2012.

[10] Summers, J., and Shah, J., 2003, “Developing measures of complexity for engineering design,” ASME 2003 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. American Society of Mechanical Engineers, 2003.

[11] Owensby, J., and Summers, J., 2014, “Assembly Time Estimation: Assembly Mate Based Structural Complexity Metric Predictive Modeling,” Journal of Computing and Information Science in Engineering 14.1 (2014): 011004.

[12] Owensby, E., 2011, “Evaluation and Comparison of Two Design for Assembly Methods: Subjectivity of Information Inputs,” ASME 2011 International Design

Engineering Technical Conferences and Computers and Information in Engineering Conference (pp. 721-731). American Society of Mechanical Engineers.

[13] Namouz, E., and Summers, J., 2014, "Comparison of Graph Generation Methods for Structural Complexity Based Assembly Time Estimation," Journal of Computing and Information Science in Engineering 14.2 (2014): 021003.

[14] Namouz, E., and Summers, J., 2013, "Complexity Connectivity Metrics– Predicting Assembly Times with Low Fidelity Assembly CAD Models," In Smart Product Engineering (pp. 777-786). Springer Berlin Heidelberg.

[15] Namouz, E., 2013, "Automated Complexity Based Assembly Time Estimation Method," CLEMSON UNIVERSITY.

[16] Mohinder, C. V. S., Sudarshan, S., and Summers, and J. D., "Structural Complexity Metrics Applied Against Product Graphs," Design Computing and Cognition'14, 2014, p. 51.

[17] Mathieson, J. L., Wallace, B. a., and Summers, J. D., 2012, "Assembly time modelling through connective complexity metrics," International Journal of Computer Integrated Manufacturing, **25**(12), pp. 1160–1172.

[18] Mathieson, J., 2011, "Connective Complexity Methods for Analysis and Prediction in Engineering Design."

[19] Mathieson, J. L., Shanthakumar, A., Sen, C., Arlitt, R., Summers, J. D., and Stone, R., 2011, "Complexity as a Surrogate Mapping between Function Models and Market Value," ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, pp. DETC2011–47481.

[20] Miller, M. G., Mathieson, J. L., and Summers, J. D., 2012, "Representation: Structural Complexity of Assemblies To Create Neural Network Based Assembly Time Estimation Models," Proceedings of the ASME 2012 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, pp. 1–11.

[21] Lindemann, U., Maurer, M., and Braun, T., "Structural complexity management– An approach for the field of product design, 2009," Springer, Berlin.

[22] Suh, N., 2005, Complexity: theory and applications.

[23] Sinha, K., and de Weck, O. L., 2013, “Structural Complexity Quantification for Engineered Complex Systems and Implications on System Architecture and Design,” ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, American Society of Mechanical Engineers, pp. V03AT03A044–V03AT03A044.

[24] Poli, C., 2001, Design for manufacturing: a structured approach.

[25] El-Haik, B., and Yang, K., 1999, “The components of complexity in engineering design,” IIE Transactions.

[26] Thoe, S., and Summers, J. D., 2013, “Correlating Problem/Process Exam Question Complexity to Anticipated Effort: A Modeling Protocol,” Volume 1: 15th International Conference on Advanced Vehicle Technologies; 10th International Conference on Design Education; 7th International Conference on Micro- and Nanosystems, p. V001T04A012.

[27] Braha, D., and Maimon, O., 1998, “The measurement of a design structural and functional complexity,” IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, **28**(4), pp. 527–535.

[28] Sinha, K., and Weck, O. de, 2012, “Structural complexity metric for engineered complex systems and its application,” In Gain Competitive Advantage by Managing Complexity: Proceedings of the 14th International DSM Conference Kyoto, Japan (pp. 181-194).

[29] Chazelle, B., and Incerpi, J., 1984, “Triangulation and shape-complexity,” ACM Transactions on Graphics (TOG).

[30] Finger, S., and Dixon, J. R., 1989, “A review of research in mechanical engineering design. Part II: Representations, analysis, and design for the life cycle,” Research in Engineering Design, **1**(2), pp. 121–137.

[31] Peak, R., Fulton, R., Nishigaki, I., and Okamoto, N., 1998, “Integrating engineering design and analysis using a multi-representation approach,” Engineering with Computers 14.2 (1998): 93-114.

[32] Summers, J., and Shah, J., 2004, “Representation in engineering design: a framework for classification,” ASME 2004 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. American Society of Mechanical Engineers, 2004.

[33] 2001, “Comparative study of representation structures for modeling function and behavior of mechanical devices,” Proc. ASME DETC, Pittsburgh, PA (2001).

[34] Bashir, H. A., and Thomson, V., 2001, “An Analogy-Based Model for Estimating Design Effort,” Design Studies, **22**, pp. 157–167.

[35] Shah, J. J., and Runger, G., 2011, “Misuse of Information-Theoretic Dispersion Measures as Design Complexity Metrics,” ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, ASME, Washington, DC, p. DETC2011/DTM–48295.

[36] Singh, G., Balaji, S., Shah, J. J., Corman, D., Howard, R., Mattikalli, R., and Stuart, D., 2012, “Evaluation of Network Measures as Complexity Metrics,” ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, ASME, Chicago, IL, pp. DETC2012–70483.

[37] Sinha, K., and de Weck, O. L., 2013, “A network-based structural complexity metric for engineered complex systems,” Systems Conference (SysCon), 2013 IEEE International, pp. 426–430.

[38] Owensby, J., 2012, “Automated Assembly Time Prediction Tool Using Predefined Mates from CAD Assemblies.”

[39] Namouz, E. Z., and Summers, J. D., 2011, “Complexity Connectivity Metrics – Predicting Assembly Times with Low Fidelity Assembly CAD Models Low Fidelity CAD Model Assembly Time Estimate : The Experiment.”

[40] Casti, J., 1979, “Connectivity, complexity and catastrophe in large-scale systems.”

[41] Simon, H. A., 1981, “The sciences of the artificial (2nd ed.),” MIT Press.

[42] Miller, M., Griese, D., Peterson, M., Summers, J. D., and Mocko, G. M., 2012, “Installation Process Step Instructions as an Automated Assembly Time Estimation Tool,” Chicago, pp. 1–8.

[43] Mathieson, J. L., 2011, “Connective Complexity Methods for Analysis and Prediction in Engineering Design,” Clemson University.

[44] Cork, R., Vaughan, R., and Humphrey, L., 1983, “Precision and accuracy of intraoperative temperature monitoring.,” Anesthesia & Analgesia.

[45] Carlson, M. D. A., and Morrison, R. S., 2009, “Study design, precision, and validity in observational studies.,” Journal of palliative medicine, **12**(1), pp. 77–82.

[46] Mohideen, U., and Roy, A., 1998, “Precision Measurement of the Casimir Force from 0.1 to 0.9 μ m,” Physical Review Letters.

[47] Stone, R., and Wood, K., 2000, "Development of a functional basis for design," Journal of Mechanical design, 122(4), 359-370.

[48] "Assembly - Definition from Model Based Enterprise Dictionary" [Online]. Available: http://www.action-engineering.com/MBEDictionary/Definitions_ListDB.php?SO=1&UID=1048&Term=Assembly&&CD=1&AD=&FD=.

[49] Sridharan, P., and Campbell, M., 2005, "A study on the grammatical construction of function structures," AIE EDAM.

[50] Thoma, J., 1975, Introduction to Bond Graphs and their Applications, Pergamon Press, New York, NY.

[51] Summers, J. D., Bettig, B., and Shah, J. J., 2004, "The design exemplar: a new data structure for embodiment design automation," Journal of mechanical design, **126**(5), pp. 775–787.

[52] Bettig, B., and Shah, J. J., 2001, "Derivation of a Standard Set of Geometric Constraints for Parametric Modeling and Data Exchange," Computer-Aided Design, **33**, pp. 17–33.

[53] Summers, J. D., Divekar, A., and Anandan, S., 2006, "Towards establishing the design exemplar as a CAD query language," Computer-Aided Design and Applications, **3**(1-4), pp. 523–532.

[54] Luger, G., and Stubblefield, W., 1989, Artificial Intelligence and the Design of Expert Systems, Benjamin/Cummings Pub. Co., Redwood City, CA.

[55] Mathieson, J. L., and Summers, J. D., 2010, "Complexity Metrics for Directional Node-Link System Representations: Theory and Applications," ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, ASME, Montreal, Canada, pp. DETC2010–28561.

[56] Mathieson, J., 2009, "Information Generation in the Design Process," ASME 2009 ….

[57] Barclay, L., and Dann, Z., 2000, "New-product-development performance evaluation: a product-complexity-based methodology," Science, Measurement and Technology, IEE Proceedings-. Vol. 147. No. 2. IET, 2000.

[58] Mathieson, J., and Summers, J., 2009, "Relational DSMs in Connectivity Complexity Measurement," Proceedings of 11th International DSM Conference (pp. 15-26).

[59] Pramanick, I., and Ali, H., 1994, "Analysis and experiments for a parallel solution to the all pairs shortest path problem," Circuits and Systems, 1994. ISCAS'94., 1994 IEEE International Symposium on (Vol. 1, pp. 479-482). IEEE.

[60] Goldberg, A., and Tarjan, R., 1988, "A new approach to the maximum-flow problem," Journal of the ACM (JACM).

[61] Freeman, L., 1977, "A set of measures of centrality based on betweenness," Sociometry.

[62] Watts, D. J., and Strogatz, S., 1998, "Collective Dynamics of 'Small-World' Networks," Nature, **393**(6), pp. 440–442.

[63] Bader, G., and Hogue, C., 2003, "An automated method for finding molecular complexes in large protein interaction networks," BMC bioinformatics.

[64] Boothroyd, G., 1994, "Product Design for Manufacture and Assembly," Computer-Aided Design, **26**(7), pp. 505–520.

[65] Tu, J., 1996, "Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes," Journal of clinical epidemiology.

[66] Kusiak, A., 2000, Computational intelligence in design and manufacturing.

[67] Zhang, G., Patuwo, B. E., and Hu, M. Y., 1998, "Forecasting with Artificial Neural Network: The State of the Art," International Journal of Forecasting, **14**(1), pp. 35–62.

[68] Francis, L., 2001, "Neural networks demystified," Casualty Actuarial Society Forum.

[69] Bland, J. M., and Altman, D. G., 1996, "Measurement error.," BMJ (Clinical research ed.), **312**(7047), p. 1654.

APPENDIX A – MATLAB CODES

The Matlab codes used for evaluating the complexity metrics, training and testing the ANN are illustrated below. These three codes can be executed only with the aid of other Matlab codes created by James Mathieson.

A.1 EZ_ANN_Run.m

This Matlab code evaluates the twenty nine complexity metrics of the assembly models and the function structures of the twenty consumer products. This code has been created by Essam Namouz.

```
Clear CellData;
Clear Assembly;
Clear Comp Array;
Clear ElementList;
Clear pathname;
Clear filename;
Clear filelocation;
%       for i = 1:17
%       if i==1
%       Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\01_crest_toothbrush.xlsx');
%       elseif i==2
%       Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\02_dewalt_sander.xlsx');
%       elseif i==3
%       Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\05_irobot_roomba.xlsx');
```

```
%	elseif i==4
%	Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\06_delta_nail_gun.xlsx');
%	elseif i==5
%	Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\07_juice_extractor.xlsx');
%	elseif i==6
%	Assembly=importxls ('C:\Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\11_delta_jigsaw.xlsx');
%	elseif i==7
%	Assembly=importxls ('C:\Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\12_BrotherSewingMachine.xlsx');
%	elseif i==8
%	Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\13_Blender.xlsx');
%	elseif i==9
%	Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\14_Chopper.xlsx');
%	elseif i==10
%	Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\15_Drill.xlsx');
%	elseif i==11
%	Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\16_HolePunch.xlsx');
%	elseif i==12
%	Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\17_IndoorElectricGrill.xlsx');
%	elseif i==13
```

```
%	Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\18_Maglight.xlsx');
%	elseif i==14
%	Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\19_Mouse.xlsx');
%	elseif i==15
%	Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\20_SolarYardLight.xlsx');
%	elseif i==16
%	Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\21_stapler.xlsx');
%	elseif i==17
%	Assembly=importxls ('C: \Users\Sri Ram\Documents\Function
structures\James_ExcelSheets\22_Vise.xlsx');
%	end
%	end
%	fprintf ('This is for product %f \n', i);
%	Assembly=importxls ('C: \Documents and Settings\enamouz\My
Documents\Dropbox\EZ_Complexity_DFA_Work\Complexity
Graphs\BoothroydPiston_basic.xlsx');
%Assembly=importxls ('C: \Users\enamouz\Desktop\TTi\R2401\EZ_Connectivity.xlsx');
% Assembly=importxls ('C:
\Users\enamouz\Desktop\ME402_TTI\connectivitygraphs.xlsx');

[Filename, pathname, type]=uigetfile ('*.xlsx','Pick an excel file');
Filelocation=strcat (pathname, filename);
Assembly=importxls (filelocation);
[CompArray, CellData, ElementList]=compag (Assembly);
%	SW_ANN_Assem_Time_Predictor (CompArray);
```

% end

A.2 TrainArchPop.m

This Matlab code trains the artificial neural networks (ANNs) for predicting the performance values (assembly time and market value) of the fifteen training products. This code has been generated by Essam Namouz.

```
function [tNet] = trainArchPop (input_filename) %changed from trainArchPop
(input_filename, arr_vec, replicate)

arrs = populate Architectures;

%       arr_vec=input (‘which architectures would you like to use?');
arr_vec=1:189;
Replicate=100;
%       replicate=input ('How many replications would you like to use?');
num_arch = size (arr_vec, 2); %this code checks the size of the vector, in case it’s not 5

%%%  These file names should be specified based on the desired training set
input_filename = 'FunctionStructures_AssemblyTime';        %Name of file that holds
inputs and targets
input_file_type = '.xlsx';        %should be xlsx, file type of inputs and targets
%       input_file_location = 'C:\Users\enamouz\Google Drive\School Stuff\PhD
Stuff\EZ_Boothroyd DFA Times for Essam\'; %file location
%       input_file_location = 'C:\Users\enamouz\Desktop\ME402_TTI\'; %file location
input_file_location = 'C: \Users\Sri Ram\Documents\';
input_xls_file = strcat (input_file_location, input_filename, input_file_type);
```

```
% training filename = strcat (input_file_location, input_filename, '_ANN_training');
%this line makes a ANN training file for given architectures
% file type = '.mat';

NN_input = xlsread (input_xls_file,1);        %This lines read in the inputs to train the
ANNs
NN_target = xlsread (input_xls_file,2)';      %This line reads the target values to train
the ANNs

size_Input = size (NN_input);
size_Target =size (NN_target);
if size_Input ~= size_Target   %This checks to make sure rows and columns of inputs and
targets match
        NN_target = NN_target';
end

tic; %Start Timing
for arr = 1: num_arch
        Si=arrs{arr_vec(arr)}                  %gets defined characteristics from above

        for rep = 1 : replicate        %this loop creates # of reps neural networks based on
the given characteristics

        tNet(arr,rep).net = newcf(NN_input,NN_target,Si);  %newcf creates a cascade-
forward back propagation network: see help newcf for more info
tNet (arr, rep).net.trainParam.showWindow = false;
tNet (arr,rep).net = train(tNet(arr,rep).net,NN_input,NN_target);    %%This retrains the
network the specified amount of times to generate pdfs
```

```
end

end

%Stop timing
time = toc;
time = time/60;
fprintf ('ANN took %f minutes to train', time);
save('Training_FS_AT','tNet')
%	Create a variable output with the results of specified architectures

%	for i=1:num_arch*replicate
%	output (i, :) = tNet (i).net (NN_input)
%	end

%%For probability density function of each architecture use
%	[f, xi] =ksdensity (output (:, 1)
```

A.3 analyzeANN.m

The purpose of this Matlab code is to test the artificial neural networks (ANNs) previously trained for predicting the performance value estimates. This code has been created by Essam Namouz.

```
Clear output;
Clear output_trainingset;
%	input_filename = 'EZ_DFA_Training_Case6_Partially_Defined';
%	input_filename = 'EZ_DFA_Training_Case_TTI_Design
%	input_filename ='EZ-Summary of BD Time Estimates';
%	input_filename = 'Complexity_Summary';
%	input_filename = 'TTIplusCEDAR';
```

```
%	input_filename = 'connectivity';
input_filename = 'Test_FS_AT';
%	input_filename = 'Complexity_Results_Conceptual_Design';
%	input_filename='TTi_Complexity_Summary';
input_file_type = '.xlsx';
%	input_file_location = 'C:\Documents and Settings\enamouz\My
Documents\Dropbox\EZ_Complexity_DFA_Work\DFA_Training_Case6_Partially_Defi
ned\';
%	input_file_location = 'C:\Users\enamouz\Desktop\TTi\';
%input_file_location='C:\Users\enamouz\Documents\Dropbox\EZ_Complexity_DFA_W
ork\';
%	input_file_location='C:\Users\enamouz\Google Drive\School Stuff\PhD
Stuff\EZ_Boothroyd DFA Times for Essam\';
%	input_file_location =
'C:\Users\enamouz\Desktop\ME402_TTI\TeamBSemesterFinalRyobiDrill\';
input_file_location = 'C: \Users\Sri Ram\Documents\';
input_xls_file = strcat (input_file_location, input_filename, input_file_type);
%NN_input = xlsread (input_xls_file,1);
%NN_target = xlsread (input_xls_file,2)';
tic;
NN_test_input = xlsread (input_xls_file, 1);
%NN_test_input2 = xlsread (input_xls_file, 1);
for i=1:18900
	output(i,:)= tNet(i).net(NN_test_input);
end
%Stop timing
time = toc;
time = time/60;
fprintf('ANN took %f minutes to test’, time);
```