ABSTRACT
As more companies and researchers become interested in understanding the relationship between product design decisions and eventual environmental impact, proposed methods have explored meeting this demand. However, there are currently limited methods available for use in the early design phase to help quantify the environmental impact of making design decisions. Current methods, primarily vetted Life Cycle Assessment (LCA) methods, require the designer to wait until later in the design phase, when a product's design is more defined; alternatively, designers are resigned to relying on prior sustainable design experience and empirical knowledge. There is a clear need to develop methods that quantitatively inform designers of the environmental impact of design decisions during the early design phase (particularly during concept generation), as this allows for reexamination of decisions before they become costly or time-intensive to change. The current work builds on previous research involving the development of a search tree of sustainable design knowledge, which, applied during the early design phase, helps designers hone in on the impact of product design decisions. To assist in quantifying the impact of these design decisions, the current work explores the development of a weighting system associated with each potential design decision. The work presented in this paper aims to quantify the general environmental impact potential design decisions have on a consumer product, by using a multi-layer perceptron neural network with back propagation training—a method of machine learning—to relate the life-cycle assessment impact of 37 case study products to product attributes. By defining the relationship between LCA data and product attributes, designers in the early design phase will be more informed of which product attributes have the largest environmental impact, such that the designer can redesign the product to have reduce this impact.
INTRODUCTION

Currently, there are significant barriers to implementation that impede the widespread development of sustainable products. This work focuses on one of these challenges—the need to inform designers about the downstream environmental ramifications of design decisions made during the early design phase, specifically before and during conceptual design. While there has been a great deal of effort dedicated to determining the environmental impact of products using Life Cycle Assessment (LCA) [1,2], these quantitative methods are only applicable during the latter phases of product design, once design decisions (such as part geometry, material selection, location of manufacturing and assembly, and product use scenarios) are fully formulated. In this sense, LCA is an \textit{a posteriori} method, and is not applicable during the early design (product ideation) phase. Considering this, there currently exist few methods commensurate with the depth of LCA that are specifically designed to inform product developers of the environmental impact of design decisions as those decisions are being made.

Current LCA methods include, but are not limited to CML, Eco-indicator 99, ReCiPe, and TRACI [3–6]. LCA methods generally are embodied in commercial software, with each method having their own strengths and weaknesses, as well as the optimum point at which they can be used in the design process. Some LCA methods involve the calculation of mid-point and end-point metrics: mid-point metrics are generally more robust and offer empirical data about the chemical environmental outputs of a product; end-point metrics are normalized from the mid-point metrics. This normalization provides the end-point metrics with a more simplified, but an easy-to-understand measure of environmental impact.

Some design methods, such as applying sustainable design guidelines [7–11] and Environmentally-Conscious Quality Function Deployment (ECQFD) [12–15] are employable during early conceptual design. However, these methods are not designed to yield a quantitative assessment; rather they help to integrate sustainability considerations into the early design process. Environmentally Responsible Product Assessment (ERPA) is a quantitative matrix method the explores the environmental impact of the individual life-cycle phases of a product [16]. Simplified LCA (SLCA) methods are tailored, streamlined methods—essentially skeletonized LCA—that are much less costly to perform and require less input information. While both the ERPA and SLCA methods are designed to be less costly and time-consuming than traditional LCA, they have distinct shortcomings; both require many design decisions to be fully clarified in order to be useful, precluding their use as part of a conceptual design method. Furthermore, SLCA methods are not widely applicable to many different types of products, and must be tailored for use [17,18]. There is a clear research gap in sustainable design methods that are both in-depth and accurate (and readily available for the design of varied consumer goods), yet are applicable before and during the concept generation phase of design.

Recent research has focused on bridging the gap between high-fidelity LCA methods in the detail design phase and the open design space in the early design phase, as 80% of the environmental impact is determined after 20% of the design process is complete [19]. However, there is accordingly less product information on which to base an LCA during the conceptual design process, when design decisions are still being clarified.

Previous research has explored LCA estimation to bring LCA data into the early design phase. In LCA estimation methods, product attributes are correlated with known LCA data to estimate the impact of similar products. Estimations can be linked manually by grouping similar products together and making assumptions based on their LCA data. These assumptions can then be used to estimate how a particular product impacts the environment in a given life-cycle phase [20].

It is important to consider that LCA has associated uncertainty. LCA estimation methods, and any method that requires estimating any parameters necessary to complete the LCA (such as component weights, distance to transport products, etc.) introduce uncertainty that can impact the accuracy of the analysis. While uncertainty in LCA is not explicitly treated in this work (but is reserved for more advanced, future research), it is the relative changes in LCA metrics across products and product attributes—not the absolute metric values themselves—that are important in the conducted analysis.

Our means of overcoming these issues is to incorporate machine learning to assist in finding correlations between product attributes and the environmental impacts calculated through performing LCA. The machine learning approach can facilitate taking product-specific data generated during conceptual design and then making informed estimations from that knowledge. In this work, the machine learning method employed is a traditional multi-layer perceptron network, commonly known as an artificial neural network. In related research, artificial neural networks are applied to families of similar products, learning the correlation between product attributes and LCA data [21–23]. However, this previous research does not look at a wide variety of products, and the resulting method is only applicable to small selection of products. The current work seeks to understand this relationship to inform a design method that can be applied to the development of widely varying consumer products.

The goal of this research is to help inform designers of the environmental impact their design decisions as they are making them. To accomplish this, the project is split into two parts: (1) the creation of a sustainable design decision engine and (2) an environmental impact analysis related to those decisions. The research presented in this paper links LCA data of consumer products to product attributes, and eventually to potential conceptual design decisions. To accomplish this, a series of 37 consumer products were analyzed using three different LCA methods, resulting in a database of material data, manufacturing data, CAD models, and 22 LCA metrics for each.
product. The 37 products were selected to reflect a large variety of consumer products based on the inferred complexity of the product (number of parts), and the impact of the use phase. The diverse variety of consumer products in the repository allows the neural net to draw conclusions about the similarities of the products, and decide how these similarities relate to environmental impact. The products used in this work are listed in Table 1.

<table>
<thead>
<tr>
<th>#</th>
<th>Product</th>
<th>#</th>
<th>Product</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cast Iron Skillet</td>
<td>19</td>
<td>Spring Drive</td>
</tr>
<tr>
<td>2</td>
<td>Soda Can</td>
<td>20</td>
<td>Apple Peeler Corer</td>
</tr>
<tr>
<td>3</td>
<td>Plastic Bottle</td>
<td>21</td>
<td>Mechanical Calculator</td>
</tr>
<tr>
<td>4</td>
<td>Scissors</td>
<td>22</td>
<td>Hand Gun</td>
</tr>
<tr>
<td>5</td>
<td>Kayak</td>
<td>23</td>
<td>Hand Dryer</td>
</tr>
<tr>
<td>6</td>
<td>Disposable Battery</td>
<td>24</td>
<td>Single Serve Coffee Maker</td>
</tr>
<tr>
<td>7</td>
<td>Toothbrush</td>
<td>25</td>
<td>Oil Lamp</td>
</tr>
<tr>
<td>8</td>
<td>Vacuum</td>
<td>26</td>
<td>3D Printer</td>
</tr>
<tr>
<td>9</td>
<td>Office Chair</td>
<td>27</td>
<td>Tattoo Gun</td>
</tr>
<tr>
<td>10</td>
<td>Coffeemaker</td>
<td>28</td>
<td>Toaster</td>
</tr>
<tr>
<td>11</td>
<td>Stapler</td>
<td>29</td>
<td>Blender</td>
</tr>
<tr>
<td>12</td>
<td>Lamp</td>
<td>30</td>
<td>Motorcycle Helmet</td>
</tr>
<tr>
<td>13</td>
<td>Game Boy</td>
<td>31</td>
<td>Mechanical Pencil</td>
</tr>
<tr>
<td>14</td>
<td>Electric Chainsaw</td>
<td>32</td>
<td>Electric Tea Kettle</td>
</tr>
<tr>
<td>15</td>
<td>Drill- Battery pack</td>
<td>33</td>
<td>Razor Scooter</td>
</tr>
<tr>
<td>16</td>
<td>Drill- Corded</td>
<td>34</td>
<td>R/C Car</td>
</tr>
<tr>
<td>17</td>
<td>“Big Wheel” Toy</td>
<td>35</td>
<td>Electric Shaver</td>
</tr>
<tr>
<td>18</td>
<td>Bicycle</td>
<td>36</td>
<td>Lawn Mower</td>
</tr>
<tr>
<td>19</td>
<td>Single Serve Coffee Maker</td>
<td>37</td>
<td>Electric Guitar</td>
</tr>
</tbody>
</table>

In addition, each product was analyzed using a previously-developed decision engine (The GREEn Quiz [24]) to determine the breadth of potential design decisions that would contribute to the environmental impact of the product through a theoretical redesign. Then, products were partitioned into product attribute bins, such that products with similar attributes are co-located; 20 product attribute groups were selected, including parameterized product size, the use of batteries, and many others. As a first step in developing a weighting system for the decision engine, a neural network approach was applied to each product attribute partition, using both LCA metrics and product attributes.

The following sections include the methodology for selecting and acquiring the LCA data, as well as the structure of the artificial neural network, results from building the neural network and correlating product attributes to their respective environmental impact, and a concluding discussion.

**METHODOLOGY**

As a first step in linking design decisions to life-cycle impacts, the relationship between product attributes and LCA impacts must be established, requiring data collection. In this section, a description of the developed decision engine is discussed, followed by methods of acquiring LCA data and product attributes, as well as an overview of the artificial neural network used to relate the two sets of data. The scope of this work assumes that the engineering designer has purview over the lifecycle impact of a product through design. It is important to acknowledge that other impacts generated in the product development process—such as business practices—can occur yet are not considered in the proposed method.

1. **Decision Engine Approach (The GREEn Quiz)**

The goal of this work is to provide design decisions to designers developing new and redesigned consumer products, such that designers will reduce the environmental impact of products throughout the conceptual design phase. The objective is to inform designer on their decisions by linking quantitative values based on vetted LCA metrics to design decisions as the designer is making them.

To achieve this, a great deal of information must be collected and synthesized to inform the method. The collection of sustainable design knowledge will consist of information related to (A) Sustainable Design Guidelines, including Design for End of Life and Use Phase impacts [8,9,11,28–30], (B) Design Heuristics, including Design for the Environment and Design for Manufacturing [31–37], (C) International Design Standards [30,38–40], (D) Customer Preference for Sustainable Products [41–47], (E) Product Cost [48], and (F) Existing Sustainable Design Methods [12–18,27,49–53]. While the listed references are exploratory in nature and are not assumed to be exhaustive, they represent the availability of information relating to sustainable design.

In order to effectively make sustainable design decisions easily accessible to designers, a web-based quiz was developed as the physical embodiment of the sustainable design decision engine. The quiz is organized in the form of a search tree, such that as a designer progresses through the quiz, only relevant queries will be presented to the user. Throughout the quiz, users select Likert-style responses to design queries. Likert-style responses were chosen to provide a set of potential user responses, such that responses are easily classified and quantified during post-processing. Means of reporting the effects of potential design decisions must be developed such that the user can understand the relationship between their design decisions and the eventual environmental impact of the product being designed. When a user has completed traversing the search tree of queries, a final report will indicate a top percentage of queries for which the user did not respond indicating the most environmentally-friendly choice. In addition to showing the user which responses could be improved, the user will be provided with a list of potential design decisions that can directly lead to an improvement in response. For example, if a user answers the question, “Will disposable batteries be used to power the product?” with “Disposable batteries will power the product and will require replacement throughout the product’s useful life”; the final report will indicate that this response is indicative of a design...
decision that will likely lead to an increased environmental impact. The report will also suggest that the user make alternative design decisions, such as including a rechargeable battery with an adapter input, reducing the power use of the device through functional redesign, or consider using alternative forms of energy to power the device.

2. Need for informed weighting system
In order for the results page to show the most relevant information, resulting scores need to represent actual environmental impact data. To address this, each query in the decision engine needs to have an associated informed weight. The goal of this paper is to take the first steps in determining these design decision weights by applying machine learning, in the form of an artificial neural network. In order to perform analysis using a neural net, LCA metric data must be collected.

3. Life Cycle Assessment Methods
Three different LCA methods were specifically selected for the development of the product metrics in this work, based on variation in fidelity, applicability, and availability. The selected methods, Eco-Indicator 99, ReCiPe (embedded in GaBi software), and Solidworks Sustainability, are prominent methods that represent the breadth of current LCAs. Descriptions of each of these methods are given as follows:

3.1. Eco-Indicator 99
Of the three methods employed, Eco-Indicator 99 (EI99) provides the simplest way to observe product impact without the need for software. EI99 looks into the impact a product can have on the environment, which is comprised of three components: Ecosystem Quality, Human Health, and Resources [4].

EI99 provides milliPoint (mPt) values for products based on their environmental impact; a higher mPt value correlates to a greater environmental impact. Three categories of environmental impact were created for the sustainable design repository: production/processes, use phase, and end-of-life. The mPt values for production/processes describe the impact of creating a product, the use-phase values describe the impact of using a product on a yearly basis, and the end-of-life values show the impact of disposing of a product, often times with the assumption that the product will end up in a landfill.

As some mPt values for materials and processes are not available in the EI99 manual, these must be estimated or determined using another source, such as Matbase [25]. For materials where no information could be retrieved from either the manual or Matbase, the mPt value was estimated based on similarities to other materials and processes.

3.2. GaBi (ReCiPe)
ReCiPe is the most in-depth LCA method used in this work. ReCiPe employs 21 LCA metrics that are used to describe the environmental impact of each of the products. Of the 21 metrics, three of them are “end-point” indicators and 18 are “mid-point” indicators [5]. The mid-point indicators measure specific emissions (such as CO₂) of each product. The end-point indicators are normalized from the 18 mid-point indicators into easy-to-understand metrics. In order to implement the ReCiPe method, a software called GaBi is used [26]. GaBi provides a graphical platform that allows the user to input various product attributes, such as parts, weight, manufacturing processes, and disposal methods. Using these attributes, GaBi is able to apply the ReCiPe method and output the 21 related metrics.

In GaBi, each product was evaluated using the information from the created sustainable design repository; this information includes: materials, manufacturing methods, weight, number of parts, and disposal method. GaBi works by figuratively connecting the materials to their manufacturing methods, then finally to their disposal methods. From there, the user inputs secondary resources, defined by GaBi, for the manufacturing processes. For example, injection molding requires tap water and electricity to complete the molding process. GaBi includes an extensive database that provides the appropriate inputs and outputs of each manufacturing process. However, reasonable assumptions were made if GaBi did not have the appropriate material or process for a product. In addition to providing material and process information, GaBi has ample information on a variety of resources. These resources, such as electricity, allow the user to identify where production is taking place, and what emissions are tied to that resource. After the user connects all the processes and secondary resources, weights for each material can be defined for each process. When all of the weights for each manufacturing process are defined, GaBi can implement the ReCiPe LCA method to determine the environmental impact.

For the ReCiPe method, GaBi displays 13 mid-point metrics instead of 18. The GaBi software combines some of the mid-point metrics into a single metric. The metrics that are combined all share the same unit of measurement; by combining some of the metrics, GaBi creates a “global” metric. The 13 mid-point metrics displayed by GaBi are shown in TABLE 2.

<table>
<thead>
<tr>
<th>#</th>
<th>Metric</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Global Warming Potential</td>
<td>CO₂</td>
</tr>
<tr>
<td>2</td>
<td>Ozone Depletion Potential</td>
<td>CFC-11</td>
</tr>
<tr>
<td>3</td>
<td>Terrestrial Acidification Potential</td>
<td>SO₂</td>
</tr>
<tr>
<td>4</td>
<td>Freshwater Eutrophication Potential</td>
<td>P</td>
</tr>
<tr>
<td>5</td>
<td>Marine Eutrophication Potential</td>
<td>N</td>
</tr>
<tr>
<td>6</td>
<td>Global Eco-toxicity Potential¹</td>
<td>14-DBC</td>
</tr>
<tr>
<td>7</td>
<td>Photochemical Oxidant Formation Potential</td>
<td>NMVOC</td>
</tr>
<tr>
<td>8</td>
<td>Particulate Matter Formation Potential</td>
<td>PM₁₀</td>
</tr>
<tr>
<td>9</td>
<td>Ionizing Radiation Potential</td>
<td>U²³⁵</td>
</tr>
<tr>
<td>10</td>
<td>Global Land Occupation Potential²</td>
<td>m²</td>
</tr>
<tr>
<td>11</td>
<td>Mineral Depletion</td>
<td>kg of Fe</td>
</tr>
<tr>
<td>12</td>
<td>Water Depletion</td>
<td>kg of Fe</td>
</tr>
<tr>
<td>13</td>
<td>Fossil Depletion</td>
<td>kg of Oil</td>
</tr>
</tbody>
</table>

¹ Four combined metrics, 2 Three combined metrics
GaBi also displays the three end-point ReCiPe metrics. These metrics are not combined and are normalized from all 18 of the ReCiPe mid-point metrics; not just the 13 displayed by GaBi. These end-point metrics are: Damage to Human Health (DALY), Damage to Ecosystem Diversity (Species/yr.), and Damage to Resource Availability ($). Due to unavailability of related input information, global land occupation potential will not be included in this analysis.

3.3. Solidworks Sustainability

The Solidworks Sustainability method is the simplest to implement of the LCA methods used. Solidworks Sustainability uses a modified CML LCA method [3,27]. This method provides an output of four metrics: Carbon Footprint ($\text{CO}_2$), Energy Consumption (MJ), Air Acidification ($\text{SO}_2$), and Water Eutrophication ($\text{PO}_4$). The Solidworks Sustainability method is more of a comparative LCA method than a standalone LCA method; it allows the user to compare the relative change in the four metrics based on changes to material, manufacturing methods, and manufacturing locations.

In order to implement this method, product models were generated using the Solidworks CAD program. These Solidworks models provided the part weights that were used in the previous LCA methods. Each of the part models were assigned a material, life expectancy, manufacturing method, and manufacturing location. The parts of the models were assembled into the full product, use phases were added, and Solidworks Sustainability software generated the four metrics.

4. Neural Network for Product Attributes

4.1. Discussion of the neural network algorithm

The artificial neural network used in this work follows the common structure of a three-layer perceptron network, which uses a back-propagated supervised learning method. A three-layer perceptron network consist of an input layer, a hidden layer, and an output layer with each node being connected to the neighboring layer by means of a weight, as seen in FIGURE 1. The motivation for using a neural net is that machine learning methods, such as this one, are capable of mapping a set of inputs to a set of outputs which are not a linear function of each other. This feature allows for the neural net to estimate unknown non-linear functions. In the case of this work, product attributes are being mapped to LCA metrics.

Before a neural network is of use, it must go through a training process. Since this work is using supervised learning, the training process starts by initializing all the weights in the network using generated random weights. To assist in the performance of the neural net, the weight is randomly assigned a value in the range of $-\frac{1}{\sqrt{n}}$ to $\frac{1}{\sqrt{n}}$, where $n$ is the number of input nodes in the network [54]. Forward propagation is conducted, using the commonly implemented sigmoid function as the activation function.

From forward propagation, back propagation and gradient descent was used to adjust the weights in the neural net to improve the overall estimation capability of the neural network. The neural net trains on a set of data that has known inputs that correlate to a set of known outputs. During the training process, the sum-of-squares error formula is used to consider error in the network. By keeping track of the error in the system, the difference in error can be used as a stopping criterion. As the neural net trains, the error in the system should continually decrease; however, the network will reach a point where it starts to learn to the noise in the training data, rather than the general function the data follows. It is at this point where the training of the neural net is ended.

4.2. Development of product attribute partitions

In order to use the neural net algorithm as described, a set of inputs must be identified. As the first step in the overarching work to relate design decisions to life-cycle impacts, an intermediate step of mapping product attributes to LCA metrics is performed. A list of 20 quantifiable product attributes relevant to each product in the product repository is used as the input data for the neural net, as seen in TABLE 3. Product attributes were generated through the systematic application of the GREEn Quiz to each of the 37 products, and product attributes that were relevant for determining the user response to each question.

After generating the product attribute values for each product in the repository, products were then partitioned into similar attribute bins. This resulted in 60 partitioned groups, with a given product being represented in multiple groups. These bins consisted of products being grouped on a Likert-style scale; generally one to three groups were made for each of the product attributes. For example, three product groups were generated from the product attribute “Size”: Size_small, Size_medium, and Size_large. Also included in the list of 60 product attribute groups are three new attributes that are logical indicators of whether the product requires electricity, combustion, or human/no energy to operate. This partitioning assists the performance of the neural network, allowing it to learn from a set of data that includes what is assumed to be products with similar impacts.

FIGURE 1: THREE LAYER PERCEPTRON NETWORK

After generating the product attribute values for each product in the repository, products were then partitioned into similar attribute bins. This resulted in 60 partitioned groups, with a given product being represented in multiple groups. These bins consisted of products being grouped on a Likert-style scale; generally one to three groups were made for each of the product attributes. For example, three product groups were generated from the product attribute “Size”: Size_small, Size_medium, and Size_large. Also included in the list of 60 product attribute groups are three new attributes that are logical indicators of whether the product requires electricity, combustion, or human/no energy to operate. This partitioning assists the performance of the neural network, allowing it to learn from a set of data that includes what is assumed to be products with similar impacts.
TABLE 3: PRODUCT ATTRIBUTES

<table>
<thead>
<tr>
<th>Product Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>Volume of bounding box (cm³)</td>
</tr>
<tr>
<td>Mass</td>
<td>kg</td>
</tr>
<tr>
<td>Number of Parts</td>
<td>Quantity</td>
</tr>
<tr>
<td>Number of Types of Material</td>
<td>Quantity</td>
</tr>
<tr>
<td>Amount of Energy Required to Operate per Use</td>
<td>Watts/use</td>
</tr>
<tr>
<td>Lifetime</td>
<td>Years</td>
</tr>
<tr>
<td>Number of Consumables per Year</td>
<td>Quantity/Year</td>
</tr>
<tr>
<td>Number of Batteries Lifetime</td>
<td>Quantity</td>
</tr>
<tr>
<td>Percent Ferrous Metal</td>
<td>Percent total mass</td>
</tr>
<tr>
<td>Percent Non-Ferrous Metal</td>
<td>Percent total mass</td>
</tr>
<tr>
<td>Percent Plastic</td>
<td>Percent total mass</td>
</tr>
<tr>
<td>Percent Glass</td>
<td>Percent total mass</td>
</tr>
<tr>
<td>Percent Organic Material</td>
<td>Percent total mass</td>
</tr>
<tr>
<td>Percent Hazardous Material</td>
<td>Percent total mass</td>
</tr>
<tr>
<td>Percent Electrical Components</td>
<td>Percent total mass</td>
</tr>
<tr>
<td>Percent Other Material</td>
<td>Percent total mass</td>
</tr>
<tr>
<td>Number of Subassemblies</td>
<td>Quantity</td>
</tr>
<tr>
<td>Number of Stock Parts</td>
<td>Quantity</td>
</tr>
<tr>
<td>Number of Manufacturing Processes</td>
<td>Quantity</td>
</tr>
<tr>
<td>Number of Fasteners</td>
<td>Percent total mass</td>
</tr>
</tbody>
</table>

4.3. Applying Product Attributes to the Neural Network

The neural net algorithm discussed in subsection 5.1 is a general three-layer perceptron network method that uses supervised learning. To relate product attributes to LCA metrics, the neural network structure must take on a slightly altered form. The inputs to the neural network are the normalized values of the 20 product attributes shown in TABLE 3. Preliminary data found that the performance (the resulting error of the estimated output) of the neural network was greatly improved when estimating one LCA metric at a time, which is why a single metric is used in training and estimating. The output data is also normalized to increase performance. In order to successfully link product attributes to life-cycle data, all 60 partitioned product groups are used to estimate a single LCA metric. This is then repeated for the remaining 22 LCA metrics.

To further improve the performance of the neural net, a dynamic scaling feature, $\eta$, was added to the algorithm to replace a static parameter. The dynamic scaling feature operates by allowing the neural net multiple attempts at reducing the error of the network for a given scaling value $\eta$. When the maximum number of attempts limit is reached, then $\eta$ will be scaled by a predetermined value, with the attempts counter then being reset. The new $\eta$ value then has a similar number of chances to successfully reduce the error of the network. This continues to repeat until either the error is successfully decreased or a number of error reductions are met. If the code is successful in reducing the error, $\eta$ is reset to its initial value and the attempt counters are reset. If the error does not decrease by the time the maximum number of attempts is made and the number of $\eta$ reductions reaches a predetermined value, then the algorithm has reached its stopping criterion.

4.4. Training the Neural Network

The neural network was trained to the products in the 60 attribute groups along with a network trained to each of the LCA metrics. Due to a limited number of data points, a series of average values for each group was generated to create a validation case. The validation data is generated by taking the average of each input data (product attributes) and output (LCA metric), to create a synthetic product’s data set that falls within the intended product attribute group. The resultant data set is used as a stopping mechanism as described at the end of section 4.1.

PROBLEM FORMULATION

The tunable parameters used in the training of the neural network are listed in TABLE 4.

TABLE 4: NEURAL NETWORK PARAMETERS

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Hidden Layer Nodes</td>
<td>10</td>
</tr>
<tr>
<td>Number of Training Iterations</td>
<td>20</td>
</tr>
<tr>
<td>Beta Multiplier in Sigmoid Function</td>
<td>1</td>
</tr>
<tr>
<td>Scaling Feature $\eta$</td>
<td>0.01</td>
</tr>
<tr>
<td>Maximum Number of Tries</td>
<td>500</td>
</tr>
<tr>
<td>Number of $\eta$ reduction</td>
<td>6</td>
</tr>
<tr>
<td>$\eta$ Multiplier</td>
<td>0.1</td>
</tr>
</tbody>
</table>

RESULTS

To assist in making a connection between design decisions and life-cycle impacts, an intermediate step of linking product attributes to LCA data was performed. The neural net was trained on the set of product attributes detailed in TABLE 3 and was used to estimate the value of a single LCA metric at a time. Using input data from organized product attribute bins allowed for 60 groups of products to be correlated to 22 LCA metrics individually. The resulting analysis generated a table of percent error for the effectiveness of the neural net. The error was calculated by taking the known output data and comparing it to the estimated value obtained from the neural net. A sample of these results are given in TABLE 5. The percent error values calculated are low, with the majority of the error values below 1%. The low error values in this data can be attributed to the effectiveness of the product grouping. The results obtained in
this work shows a promising preliminary result for estimating products based on their product attributes.

**TABLE 5: SELECTION OF ESTIMATED LCA METRIC PERCENT ERROR DATA**

<table>
<thead>
<tr>
<th>Product Attribute Group</th>
<th>ReCiPe: CO2</th>
<th>EI99: Use</th>
<th>SolidWorks: Energy Consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size_Large</td>
<td>1.12E-04</td>
<td>6.83E-06</td>
<td>9.26E-03</td>
</tr>
<tr>
<td>Mass_Medium</td>
<td>1.18E-06</td>
<td>1.80E-02</td>
<td>1.81E-02</td>
</tr>
<tr>
<td>Number of Parts Few</td>
<td>5.28E-02</td>
<td>5.93E-02</td>
<td>1.19E-01</td>
</tr>
<tr>
<td>Number of types of material_Some</td>
<td>1.51E-05</td>
<td>2.03E-02</td>
<td>2.75E-05</td>
</tr>
<tr>
<td>Electrical Energy_Yes</td>
<td>2.93E-07</td>
<td>4.04E-05</td>
<td>5.80E-05</td>
</tr>
<tr>
<td>Combustion_No</td>
<td>1.03E-04</td>
<td>3.87E-02</td>
<td>1.00E-06</td>
</tr>
<tr>
<td>Energy per use_Some</td>
<td>3.03E-06</td>
<td>1.19E-03</td>
<td>2.54E-02</td>
</tr>
<tr>
<td>Lifetime_Medium</td>
<td>9.71E-07</td>
<td>5.39E-06</td>
<td>1.73E-05</td>
</tr>
<tr>
<td>Number of Consumables_A lot</td>
<td>8.74E-07</td>
<td>3.85E-02</td>
<td>5.56E-02</td>
</tr>
<tr>
<td>Number of Batteries_None</td>
<td>1.33E-05</td>
<td>1.87E-01</td>
<td>5.24E-04</td>
</tr>
<tr>
<td>Percent Ferrous Metal_Majority</td>
<td>4.09E-03</td>
<td>1.23E-01</td>
<td>1.15E-01</td>
</tr>
<tr>
<td>Percent Non_Ferrous Metal_Some</td>
<td>2.01E-05</td>
<td>1.46E-07</td>
<td>8.15E-08</td>
</tr>
<tr>
<td>Percent Plastic_Majority</td>
<td>2.52E-06</td>
<td>6.92E-06</td>
<td>1.31E-06</td>
</tr>
<tr>
<td>Hazardous Material_Yes</td>
<td>2.87E-04</td>
<td>6.07E-02</td>
<td>1.12E-03</td>
</tr>
<tr>
<td>Electrical Components_Yes</td>
<td>9.60E-03</td>
<td>1.29E-03</td>
<td>8.12E-02</td>
</tr>
</tbody>
</table>

**CONCLUDING DISCUSSION**

In completing the Life Cycle Assessments for the 37 products, we learned a great deal about the applicability of each method. The use of EI99 was straightforward for most of the products in the sustainable design repository. Various assumptions allowed for overcoming questions about products’ materials and processes. There is little concern about the assumptions made because they all remained consistent throughout the analysis. For example, when a material’s mPt value is not available, it is estimated and used for all products that may include that material. EI99 offers a reliable LCA method when software is not available.

Using GaBi to implement the ReCiPe method is an in-depth way to obtain a large breadth of useful LCA metric data. However, GaBi relies on a large expensive database to produce reliable data. This barrier to availability of GaBi makes this method not accessible for all designers.

The Solidworks Sustainability method was the easiest to use, allowing designers to subject early-stage CAD concepts to a comparative LCA method. Though the method is shallow with respect to metrics and manufacturing methods, it is one of the only LCA methods that can be successfully implemented as design changes are still being made. This method is also one of the only methods that provide a sustainability incentive and highlights more sustainable alternatives, in regards to material, manufacturing processes and manufacturing locations.

The process of creating a working neural network has revealed some interesting aspects of the repository LCA data. For example, during the process of developing the methodology of this work, it was found that neural network could only effectively handle one LCA metric at a time. Based on the results that were obtained, the use of an artificial neural network has shown that LCA estimations through machine learning can provide an effective method for linking product attributes to life-cycle impacts.

**ACKNOWLEDGMENTS**

This work was funded by the National Science Foundation NSF CMMI-1350065 and Oregon State University's School of Mechanical, Industrial, and Manufacturing Engineering.
## APPENDIX A

### TABLE 6: FULL LIST OF PRODUCT ATTRIBUTES

<table>
<thead>
<tr>
<th>Product Attribute Group</th>
<th>Range</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size_Large</td>
<td>&gt;100000</td>
<td>cm³</td>
</tr>
<tr>
<td>Size_Medium</td>
<td>10000 to 100000</td>
<td>cm³</td>
</tr>
<tr>
<td>Size_Small</td>
<td>&lt;10000</td>
<td>cm³</td>
</tr>
<tr>
<td>Mass_Large</td>
<td>&gt;10</td>
<td>kg</td>
</tr>
<tr>
<td>Mass_Medium</td>
<td>1-10</td>
<td>kg</td>
</tr>
<tr>
<td>Mass_Small</td>
<td>&lt;1</td>
<td>kg</td>
</tr>
<tr>
<td>Number of Parts_A lot</td>
<td>&gt;40</td>
<td>Number</td>
</tr>
<tr>
<td>Number of Parts_Medium</td>
<td>20 to 40</td>
<td>Number</td>
</tr>
<tr>
<td>Number of Parts_Few</td>
<td>&lt;20</td>
<td>Number</td>
</tr>
<tr>
<td>Number of types of material_A lot</td>
<td>&gt;7</td>
<td>Number</td>
</tr>
<tr>
<td>Number of types of material_some</td>
<td>4 to 7</td>
<td>Number</td>
</tr>
<tr>
<td>Number of types of material_Few</td>
<td>&lt;4</td>
<td>Number</td>
</tr>
<tr>
<td>Electrical Energy_Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Electrical Energy_No</td>
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<td></td>
</tr>
<tr>
<td>Combustion_Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Combustion_No</td>
<td>No</td>
<td></td>
</tr>
<tr>
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<td></td>
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<tr>
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<tr>
<td>Energy per use_A lot</td>
<td>&gt;100</td>
<td>Watts</td>
</tr>
<tr>
<td>Energy per use_Some</td>
<td>10 to 100</td>
<td>Watts</td>
</tr>
<tr>
<td>Energy per use_Few</td>
<td>&lt;10</td>
<td>Watts</td>
</tr>
<tr>
<td>Lifetime_Long</td>
<td>&gt;5</td>
<td>Years</td>
</tr>
<tr>
<td>Lifetime_Medium</td>
<td>1 to 5</td>
<td>Years</td>
</tr>
<tr>
<td>Lifetime_Short</td>
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<td>Years</td>
</tr>
<tr>
<td>Number Consumables_A lot</td>
<td>&gt;100</td>
<td>Number</td>
</tr>
<tr>
<td>Number Consumables_Some</td>
<td>1 to 100</td>
<td>Number</td>
</tr>
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<td>Number Consumables_None</td>
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<td>Number</td>
</tr>
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<td>Number Batteries_A lot</td>
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</tr>
<tr>
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<td>1</td>
<td>Number</td>
</tr>
<tr>
<td>Number Stock Parts_A lot</td>
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</tr>
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<td>5 to 20</td>
<td>Number</td>
</tr>
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<td>Number</td>
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<td>Number</td>
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<td>Number</td>
</tr>
<tr>
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<td>Number</td>
</tr>
<tr>
<td>Number MFG Processes_Few</td>
<td>&lt;10</td>
<td>Number</td>
</tr>
<tr>
<td>Fasteners_A lot</td>
<td>&gt;1</td>
<td>Percent total Mass</td>
</tr>
<tr>
<td>Fasteners_Some</td>
<td>&lt;0 to 1</td>
<td>Percent total Mass</td>
</tr>
<tr>
<td>Fasteners_None</td>
<td>0</td>
<td>Percent total Mass</td>
</tr>
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</table>
REFERENCES


