GENETIC ALGORITHM OPTIMIZATION OF PRODUCT DESIGN FOR ENVIRONMENTAL IMPACT REDUCTION

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ABSTRACT

The growing environmental awareness of today's consumers has put the manufacturing companies with the burden of taking responsibility for their own product's environmental impact. This incited the need to develop product management systems which focus on minimizing a product's impact across its life cycle. However, a survey conducted on Malaysian design companies suggests that there are no systems available for them to include environmental considerations in their product design processes. This dissertation presents a study on product design optimization which focuses on the inclusion of the potential environmental impact in the design consideration. The aim of this research is to develop a methodology that will aid designers to reduce the potential environmental impact of a product's design, which does not require them to train additional skills in environmental impact analysis. Analysis of the effect of changing the product design parameters such as its dimensions, and basic features on the environmental impact of machining process in terms of its power consumption, waste produced and the chemicals and other consumables used up during the process is the key method in this research. A novel feature-based product design methodology based on an integrated CAD-LCA approach is developed which analyzes a product design's environmental impact. Genetic Algorithm is applied to the product design parameters to create a feedback system in order to get the best possible product design solutions with the least environmental impact within the product design functionality limitation. The results using the proposed methodology yields 50 pareto optimal design solutions for every run, allowing the designers the freedom to choose the suitable design. The developed methodology aids designers in providing design solutions that satisfies the customer requirements and at the same time adding value to their work through the suggestion of eco-friendly alternatives.

ABSTRAK

Kesedaran alam sekitar yan semakin meningkat terhadap pengguna hari ini meletakkan syarikat-syarikat pembuatan terbeban mengambil tanggungjawab terhadap impak alam sekitar produk mereka sendiri. Ini mencetuskan keperluan untuk membangunkan sistem pengurusan produk yang memberi tumpuan untuk mengurangkan kesan produk di dalam seluruh kitaran hayatnya. Walau bagaimanapun, kajian yang dijalankan ke atas syarikat-syarikat reka bentuk di Malaysia mendapati bahawa tidak terdapat sistem yang mengambil kira akan kesan alam sekitar dalam proses reka bentuk produk mereka. Disertasi ini membentangkan kajian berkenaan produk pengoptimuman reka bentuk yang mengambil kira akan potensi kesan-kesan alam sekitar dalam menimbangkan reka bentuk yang sesuai. Tujuan kajian ini adalah untuk membangunkan satu kaedah yang akan membantu pereka untuk mengurangkan potensi kesan alam sekitar untuk reka bentuk produk, yang tidak memerlukan mereka untuk menambah kemahiran tambahan semasa menjalankan analisis kesan alam sekitar. Analisis kesan perubahan parameter reka bentuk produk seperti dimensi, dan ciri-ciri asas mengenai kesan alam sekitar daripada proses pemesinan, penggunaan tenaga, sisa yang dihasilkan, bahan kimia dan bahan lain yang digunakan semasa proses adalah kaedah utama dalam kajian ini. Bagi merealisasikan kajian ini, model CAD sesuatu produk dengan senario reka bentuk yang berbeza digunakan, Analisis penggunaan tenaga yang menggunakan kesan alam sekitar kaedah kalkulator maju. Sisa yang dihasilkan, dan barangan yang digunakan seperti pelincir dan penyejuk, dianalisis dengan menggunakan faktor pelepasan alam sekitar. Kaedah pengoptimuman menggunakan Algoritma Genetik digunakan untuk parameter reka bentuk produk kaedah ini untuk mendapatkan dimensi produk terbaik yang menghasilkan kesan alam sekitar paling sedikit dalam proses pemesinan. Keputusan metodologi yang dicadangkan menghasilkan 50 pareto penyelesaian reka bentuk optimum kepada tiap larian, membolehkan pereka bentuk kebebasan memilih reka bentuk yang sesuai.

Metodologi yang dibangunkan membantu pereka bentuk memberi penyelesaian reka bentuk yang memuaskan keperluan pelanggan dan juga menambah nilai kepada kerja mereka melalui cadangan alternatif mesra alam.

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LIST OF ABBREVIATIONS

AAU	Assigned amount unit
AHP	Analytical Hierarchy Process
aLCA	Abridged Life Cycle Assessment
ANOVA	Analysis of Variance
CAD	Computer-Aided Design
CAM	Computer-Aided Manufaturing
CFD	Computational Fluid Dynamics
Chi	Chip recycling impact
Ci	Coolant consumption impact
CNC	Computer-Numeric Control
DFA	Design for Assembly
DfD	Design for Disassembly
DfE	Design for Environment
DfLC	Design for Life Cycle
DFM	Design for Manufacture
DFMA	Design for Manufacturing and Assembly
DFQ	Design for Quality
DfR	Design for Recycling
DFX	Design for X
DOE	Design of Experiments
EC	European Commission
ECM	ECODESIGN Checklist Method
ECoDE	Environmental Component Design Evaluation
EEC	Environmental European Commission
EFFRA	European Association for the Factories of the Future
Ei	Potential Environmental impact
EIA	Environmental Impact Assessment
ELV	End of Life Vehicle
EU	European Union
EuP	Energy-using products
FBD	Feature-Based Design
FEA	Finite Element Analysis
FoF PPP	Factories of the Future Public Private Partnership
GA	Genetic Algorithm

GP	Goal Programming
GQFD	Green Quality-Function Deployment
GUI	Graphic User Interface
GWP	Global Warming Potential
HOQ	House of Quality
IEC	International Electrotechnical Commission
IPCC	Intergovernmental Panel on Climate Change
IPO	Input-Process-Output
ISO	International Organization for Standardization
JEMAI	Japan Environmental Management Association for Industry
LCA	Life Cycle Analysis
LCC	Life Cycle Cost
LCI	Life Cycle Inventory
Li	Lubricant oil consumption impact
MQL	Minimum Quantity Lubricant
MRR	Material Removal Rate
NC	Numerical Control
NSGA-II	Non-sorting Genetic Algorithm 2
OECD	Organization for Economic Co-operation and Development
PILOT	Product Investigation Learning and Optimization Tool
PLM	Product Life Cycle Management
PMi	Machine power consumption impact
QFD	Quality-Function Deployment
QFDE	Quality Function Deployment for Environment
RoHS	Restriction of Hazardous Substances
S/N	Signal to Noise
SA	Simulated Annealing
SEC	Specific Energy Consumption
SETAC	Society of Environmental Toxicology and Chemistry
SME	Small and Medium-sized enterprises
TQM	Total Quality Management
TR	Technical Report
UNFCC	United Nations Framework Convention on Climate Change
WCED	World Commission on Environment and Development
WEEE	Waste Electrical and Electronic Equipment

CHAPTER 1

INTRODUCTION

This thesis is a report of the study of Product Design Optimization which integrates the environmental impact consideration of machining process with the other design considerations used by the designers. The first chapter presents the background of the study and highlights its significance. Furthermore, the deliverables of the study which are aimed to be achieved at the end of the research are established.

1.1 Background

Based from the forecast of the United Nations , the planet's population is expected to increase from today's 7 billion to approximately 8 billion by the year 2020. It is a burden, especially in the industrial sector to produce more products to meet this increasing demand, within the limit of the earth's resources. Over the last decade, environmental awareness with respect to ecological changes and natural resources depletion has been given much needed attention across many industries and government. According to Vachon (2003), one of the consequences that manufacturing industries would face in this increase of environmental awareness is the fact that their current production operations, supply chain networks, and business practices would be questioned by different stakeholders including End-customers who prefer to buy products using eco-friendly materials and processes (e.g. recycled paper, dolphin-safe tuna); Industrial and commercial customers who include environmental criteria in selecting their suppliers; Environmental advocacy groups like Greenpeace and Sierra Club, which exposes an organization's environmental malpractices; The financial division which has an increasing knowledge that adopting environmental-friendly practices would be cost-beneficial to the organization.

With these stakeholders having their eyes focused on manufacturing organizations, it is necessary for them to adopt environmental practices that would comply with the stakeholders' requirements.

Another problem for industries is the introduction of regulatory measures to ensure sustainable development such as the recent EU Draft Proposal for a directive on establishing a framework for eco-design compliance as a requirement in putting a product in the European market. With these regulations and the emergence of a new market breed, some organizations decided to step up to the challenge and seek ways to reduce environmental impact in making their products.

As engineers and academics we could respond to these challenges by research geared towards the investigation of methods to support engineers in developing environmental-friendly products and/or manufacturing processes; Impart research findings and knowledge to industrial sectors to aid them in reducing the burden placed on them by the increased awareness of stakeholders.

1.1.1 Motivations for this research

There are several motivating factors that justified the further study of this research and these can be categorized into political/legislative, industrial practice, and research trends.

1.1.1.1 Legislation

According to research conducted by NASA's climate scientists (Hansen et al., 2008), the highest possible safe amount of CO_2 in the atmosphere is 350ppm, which is way below the current atmospheric CO_2 amount of 388.92ppm as of November 2011. The warning has caught the attention of the world leaders and the Kyoto Protocol was established by the United Nations Framework Convention on Climate Change (UNFCCC) to enforce the commitment of countries to reduce the emission of Greenhouse gases (GHG) .

During the UNFCCC in Copenhagen last 2009, one of the targets of the established Copenhagen Accord (2009) is to maintain the earth's maximum temperature rise to less than $2^{o}C$. This can be achieved with the reduction of the amount of Carbon released in the atmosphere to 350ppm. With the Copenhagen Accord's implementation, government and industrial sectors are starting to count their CO_2 emissions and outlining ways to reduce their impacts.

Besides the United Nations pushing the global community to reduce its emissions, there are several policies that control the inflow of products that does not comply with given environmental standards. Especially in the European Union, there are directives that promote the sustainable production and consumption of products. The mandatory Environmental Impact Assessment (EIA) Directive (85/337/EEC) is enforced to activities that are considered to have significant effects in the environment. Another directive that is in place is the Directive on the restriction of the use of certain hazardous substances in electrical and electronic equipment (2002/95/EC), commonly known as Restriction of Hazardous Substances (RoHS). Other environmental-related legislations that manufacturers need to comply are the End of Life Vehicle (ELV) Directive, Waste Electrical and Electronic Equipment (WEEE) Directive, Energy-using products (EuP), and Packaging directive 94/62/EC to name just a few (Sadgrove, 2013)

1.1.1.2 Eco-design Practice by Malaysian companies

Such initiatives like Eco-design, Design for the Environment, Design for Recyclability, Green Supply Chain, Reverse Logistics, Product Stewardship, and/or Product Take-back have been initiated in developed countries such as Japan, Australia and European countries. Strategic measures and initiatives in developing countries on the other hand are still far behind. Incentives and initiatives by the government or the industry are still at the infancy level. Based on a pilot study on the implementation of eco design among Malaysian companies (Taha et al., 2008), it was revealed that soft regulatory controls, awareness and lack of supportive infrastructure have led to the unwillingness of Malaysian industry in initiating eco design. Eco design strategy can be classified on four different levels from redesign of product for eco compliance on the first level and radical eco innovation at the fourth level. Since Malaysian industries are still grappling with the idea of eco design, supportive infrastructure to get past the first level is needed. Recycling, reuse and remanufacture in Malaysia are still considered a by-product of waste instead of a strategic option in product design. Malaysian clean production efforts are still end pipe activities which does not considers design as the element of change. It is not yet innate to Malaysian designers to incorporate environmental impact in design consideration because there is no design methodology available to the participating design companies to assess the environmental impact during the design phase.

1.1.1.3 Research Strategies

Many Research Institutes, most importantly from the EU, have already established the importance of research on sustainable manufacturing which covers the whole supply chain from raw material, to production, distribution, consumption and disposal. The European Technology Platform "Manufuture" is an industrial-driven initiative which allows growth and sustainability in the knowledge community (Jovane et al., 2009). In this platform, they have developed a generic model of a competitive sustainable development paradigm. A specific proactive initiative to support this platform is to conduct strategic research on Knowledge-based manufacturing, with focus on Manufacturing Process Modeling and Simulation.

This action focuses on the research of applicable modelling and simulation technologies in the fields of processes with mechanical, energetic, fluidic and chemical phenomena for modelling and simulation of parts manufacturing. The simulation systems should have links to CAD-models and integration of basic analytic methodologies for engineering finite elements, mechanics and fluid mechanics, molecular dynamics or others. They have to be integrated into the manufacturing engineering chains. The models have to be evaluated by experiments.

Manufuture Annex II – Knowledge-Driven Factories

Another important effort is the OECD Project on Sustainable Manufacturing and Eco-innovation (2009) which mentions that Sustainable Manufacturing calls for multi–level eco-innovations which may shift the paradigms of conventional organization boundaries. It is anticipated that the integrated use of technologies can potentially yield higher environmental impact improvements. The European Association for the Factories of the Future (EFFRA) developed a technological roadmap called "The Factories of the Future Public Private Partnership" (FoF PPP), which addresses the development of next-generation technologies. It also addresses the need for the development of new Eco-Factory models and green product manufacturing that would allow design and production of sustainable products with drastically reduced energy consumption, and enhanced manufacturing processes. This also identified research focus on defining factors that would allow the minimization of environmental impact and resources consumption (EU-Commission, 2010).

1.2 Research Aim and Objectives

The aim of this research is to develop a methodology that will aid designers to reduce potential environmental impact of machining process in their designs. This aim can be attained by satisfying the following objectives:

1. To critically review the related literature on current eco-design methods and other secondary resources in relation to the concept of integrated solutions

2. To develop an integrated feature-based design method to assess the environmental impact of a product design, specifically on the impact of the machining process, to aid product designers.

3. To demonstrate the methodology through a case study by optimizing the design of a product according to its features with the minimization of potential environmental impact as its target objective

1.3 Scope and Limitations

The scope of Eco-design for Manufacturing Processes alone is a wide area for research and several aspects of it can be divided into different research topics. The scope of this research is to focus on one the effect of the proposed methodology to one type of manufacturing process, which is computer numerical control (CNC) machining. It deals with several metal removal processes required to achieve the desired shape of the product. In the case study that will be presented in the succeeding chapters, the material removal processes encountered are drilling and milling operations.

There has been no standard method in the collection of data for the Life Cycle Inventory and the database used in this research, specifically the environmental impact of energy consumption and waste generated (i.e. kg-CO_{2equiv}/KW-hr, kg-CO_{2equiv}/kg), are based from previously published data.

In line with the aim of the research, which is to develop a design methodology, the main focus of the research is the concept of finding design solutions that would include the environmental considerations. However, the definition of “environmental considerations" in this research is limited to the scope of machining process as mentioned. This limits the boundary of impact assessment to the amount of energy consumed during machining of the product, and the waste that is generates. An in-depth view of the "environmental considerations" boundary will be discussed in Chapter 4.

1.4 Thesis Structure

In order to present this thesis in a logical manner, this thesis is divided into six further chapters:

Chapter 2: Literature Review

This chapter aims to discuss about the general idea of Sustainable Manufacturing and the popular research areas in this field, crossing the whole product life cycle from Material Extraction to Disposal. It then narrows down to the concept of Eco-design in Product Development. In order to establish this concept, specific eco-design methods and intelligent approaches to product design optimization are reviewed. The final section of this chapter offers the research proposal which is established from the research gaps found on the literature review.

Chapter 3: Research Methodology

The aim of this chapter is explain the research approaches to be used in order to satisfy the research objectives established. This also includes the selection of methods and the justification of its necessity.

Chapter 4: Design Methodology and Development

The chapter presents the detail of the proposed design methodology and the explanation of concepts used behind. An integrated design method framework is presented and it explains the environmental impact assessment and the genetic algorithm principles.

Chapter 5: Application of the proposed model

The proposed design methodology is demonstrated using a product case study in this chapter. It shows the step-by-step procedure on the implementation of the proposal and its applicability in product design cases.

Chapter 6: Evaluation and Validation

This chapter reports the findings of the demonstrated case study from the previous chapter. A validation of the proposed design method is presented by comparison with existing design methods that were mentioned in Chapter 2.

Chapter 7: Conclusion

This chapter imparts the conclusions of this research. It shows that the research aim and objectives have been achieved and reviews the research process. The contribution to knowledge and to practitioners made by this study, and the areas for future research are identified.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

There is an increase of awareness in environmental considerations for industrial activity since the oil crisis in the 1970's. In Japan, the growing concern for the importance of energy consumption has been the basis of the "Top Runner" program. In most industrial companies, the attempt to reduce the environmental impact was focused on developing technologies that would manage, control and treat waste, popularly known as "end-pipe solutions". Then by the end of the 1970's, the concept of pollution prevention became an alternative to "end-pipe" solutions, because it is based on the belief that preventive approach is more effective, technically sound and economical than conventional pollution controls. It is different because it focuses on the solution upfront by reducing the consumption of resources through product reformulation, process modification, equipment redesign, and recycling and reuse of waste materials (Royston, 1979). In the US, companies like 3M have introduced this concept with its 3P Program (Pollution Prevention Pays) which led to the tremendous reduction of waste in the production system. So far, 3P has eliminated more than 3 billion pounds of pollution and reduced cost of $1.4 billion (3M, 2011).

These efforts however, are still not enough and threats to the environment are still growing. From the release of the Brundtland Report (1987), the scope of pollution prevention widened covering areas outside industrial activity and expanded through the complete life cycle of the product, and other activities affecting the economy, environment and society, which are now the pillars of sustainability.

Since then, it was realized that a pro-active approach in production systems through eco-design could lead to reduction of direct cost and environmental impacts. According to Brezet (1998), eco-design development is expected to continue through the 4 stages of eco-design, from product improvement to over-all production system innovation.

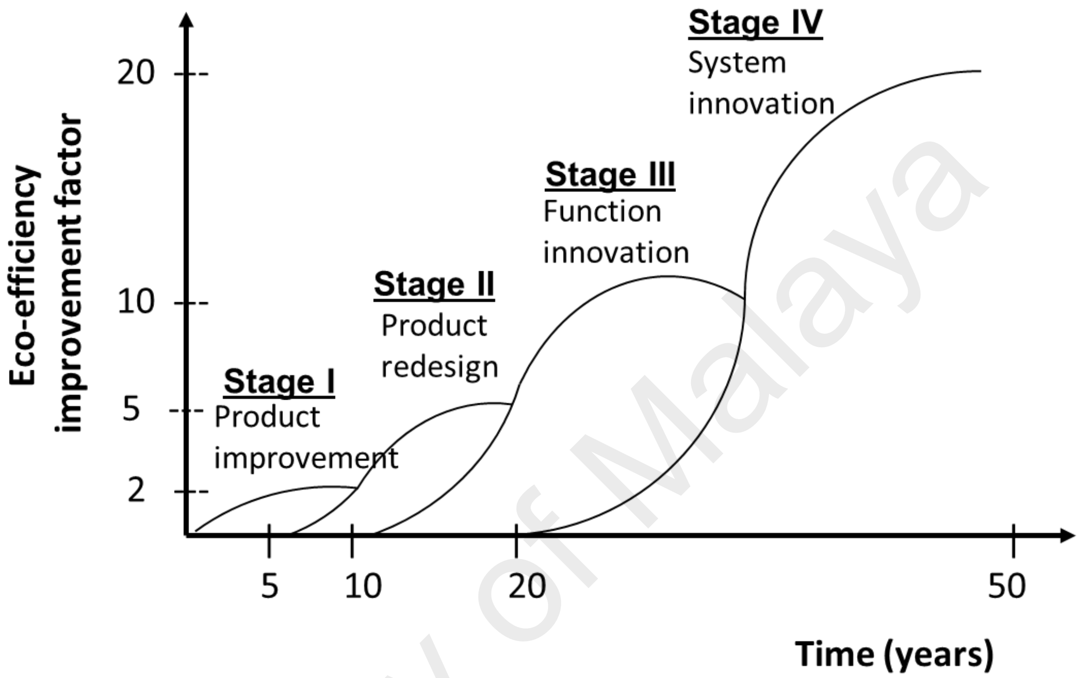


Figure 2.1 Stages of Eco-design against its eco-efficiency improvement (JC Brezet)

The four stages of eco-design are described as follows:

Stage I: Product Improvement – this is an incremental improvement of the product to comply with pollution prevention and environmental legislations and/or standards. This can be done by decreasing the use of materials or replacement of alternative to toxic material.

Stage II: Product Redesign – a new product is redesigned based on an existing concept but product parts are replaced by others. Typical approach in this stage is the reuse of raw material and spare parts. Also, the reduction of energy use at several stages of the life cycle is another approach.

Stage III: Function Innovation – this is an innovation to change the way a function is fulfilled. For example, from using paper-based information as manuals for products to web-based information dissemination.

Stage IV: System Innovation – this occurs when innovation in the production systems are required based on the new product and services. Changes in the infrastructure and/or the organization take place like changes in organizational structure, strategic planning and labor activities.

According to this model, the move from stage 1 to 4 would require a significant amount of time and complexity, but would yield higher eco-efficiency improvements. This means, in 10-20 years' time, a more complex eco-design innovation could be achieved.

With this background on eco-design, this chapter can deeply discuss some eco-design process and methods that were developed in the academia and used in the industry. A comparison of different eco-design practices will be discussed and seeks to understand their strengths and weaknesses and explore the opportunities that can be derived from them, for their improvement. To reflect the relevant aspects of eco-design with this research, this chapter is structured into sections each narrowing focus from a broader topic as shown in Figure 2.2. Section 2.2 talks about the general idea of sustainable manufacturing, which focuses on several aspects of product development, manufacture, distribution and disposal. Section 2.3 provides a closer look into sustainable manufacturing by focusing on the product development aspect, Eco-Design. Then, a detailed discussion of research trends and methods of Eco-Design are analyzed in Section 2.4 and finally, the different intelligent approaches to optimizing designs are investigated.

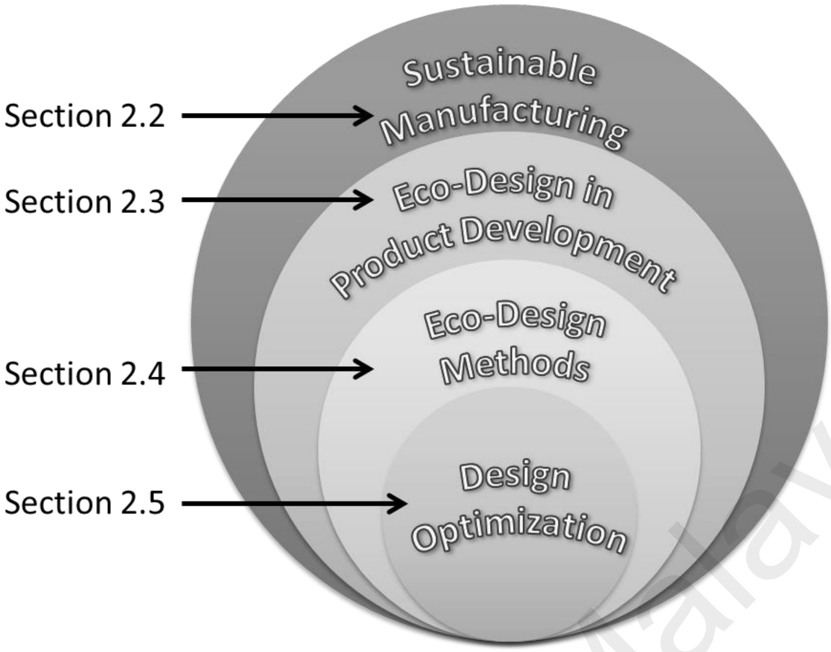


Figure 2.2 Framework of the literature review

At the end of this chapter, the theoretical framework of this research will be presented which aims to show the gaps in literature that needs to be further explored.

2.2 Sustainable Manufacturing

"Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs."

UN World Commission on Environment and Development (WCED)
"Our Common Future" (Brundtland, et al., 1987)

Since the Brundtland Report by UN WCED (1987), the concept of sustainability has received much attention from the industry and several niche research areas cropped up and diversified from their core research areas. Sustainability has many definitions with its core principles of economic balance, environmental protection, and social responsibility which lead to an improved quality of life for today and for future generations (EPA, 2009). As manufacturing companies are joining the "sustainability" bandwagon, it is fundamental to embrace these principles and integrate them in their manufacturing paradigm. The concern about environmental impact is from the fact that all products affect in some way the environment across its life span and someone has to take responsibility for it.

Thus, borrowing the UN WCED definition of sustainable development, sustainable manufacturing can be defined as the creation of goods or services that meets the demands of the present society without compromising the future generation to meet their own needs (Brundtland, et al., 1987). Previously, the focus on industrial efficiency dealt with the improvement of labor productivity. Now, the goal is resource productivity = doing more with less. This can be achieved by using (manufacturing) processes that are non-polluting, consume less energy and natural resources, lower cost, and safe for consumers, local community and employees. This is the central concept of sustainable manufacturing which aims to produce products with minimum resource consumption and waste generation (Nambiar, 2010). With the industry's increased interest on achieving a sustainable system, researchers in product development and production engineering have come up with a multitude of concepts and theories (Glavic & Lukman, 2007) in achieving a sustainable manufacturing system which revolves around the product life cycle.

2.2.1 Life Cycle Thinking

"Nature does not create waste as such. Everything in nature is used up in a closed, continuous cycle with waste being the end of the beginning."

Chef Arthur Potts-Dawson, on sustainability in restaurants

The core of eco-design (H. Brezet et al., 1997) is the concept of the product life cycle, which takes into the account the environmental aspects that occur during the complete life cycle of the product. It takes into consideration energy consumption, material usage like toxic chemical substances, product recyclability, disassemblability, packaging, transport, etc. The life cycle of a product starts from mining the raw materials needed to manufacture the product, production and assembly of products, distribution of finished goods to the consumer, using the product, until it serves its purpose and lastly to its disposal. The research on sustainable manufacturing have then diversified into different fields tackling different problem areas and very specific to a particular stage in the product's life cycle. It is actually encouraged by legislators, particularly in the European Union, which have several environmental directives in place like the Waste Electrical and Electronic Equipment (WEEE) directive, Restriction of Hazardous Substances (RoHS) and integrated pollution prevention and control (IPPC). With these emerging Product Stewardship legislations, the pressure is now put on the companies who should take responsibility for their products even outside their traditional scope of manufacturing activities and should consider the consequences that the product undergoes extending to the rest of its life cycle stages. For example, considering the waste of the packaging material used to be easily recycled when discarded by the consumer.

Figure 2.3 below highlights some popular concepts and researches in the field of sustainable manufacturing and how it is integrated into the product's life cycle. The red arrows indicate the starting point of the product life cycle, which is the natural resource, and the ending point, which is the product's disposal (end of life). Following the traditional product life cycle represented by the blue arrows, raw materials are harvested from the environment, which is then processed into products, and then distributed to the consumers for their use. At the end of its life, the products are eventually disposed. As the product goes along its life cycle, resource consumption and waste generation occurs at each stage. However, if the waste or by-products of these processes could be re-introduced back into the system, then this would close the loop and form a cycle, creating a sustainable system (called closed loop systems). Closing the gap from the disposal stage to the raw material extraction stage are the green arrows which represent the sustainable manufacturing concepts.

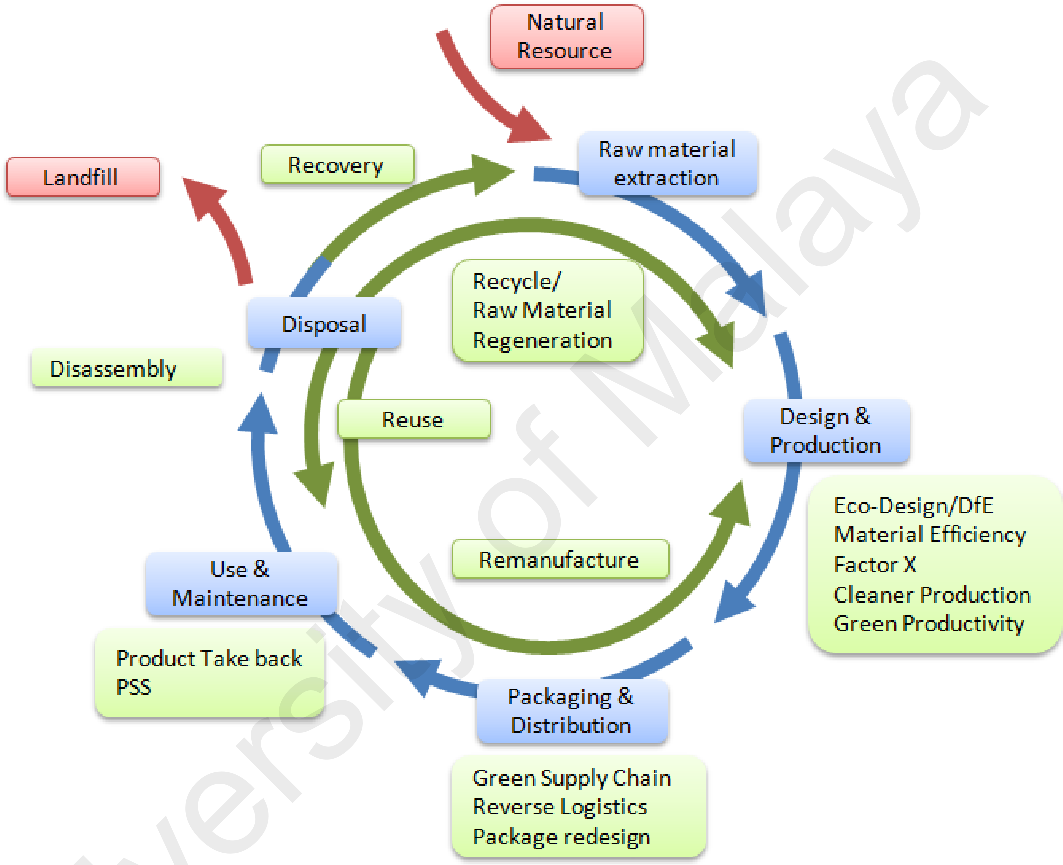


Figure 2.3 Closing the gap of a product life cycle through sustainable manufacturing

In eco-design, training product designers to think in a life cycle perspective is uncomplicated. The environmental impacts of products at each stage of the life cycle can be identified which can give focus on actions that are relevant in reducing the environmental impact. Having a life cycle perspective gives designers a holistic view of the product. Design options could have varying impacts to the environment at different life cycle stages with possible trade-offs between different designs and across the different life cycle stages. Design A could have less waste generated in the manufacturing stage, but it could consume more power during its use stage compared to Design B. Therefore, trade-offs should be examined properly and this can be done with the proper assessment methods (more about assessment methods and tools in section 2.3).

Here are some examples of design trade-offs (Pahl, 2007) that may justify one environmental impact, but may displace the impact of another criterion:

a) Using a recyclable material that would require a recycling process that results in a higher environmental impact from the combined emissions transporting the material to be recycled, the consumed energy and waste generated waste, than is saved by recovering the material.

b) Designing a smaller version of a product. It may require fewer resources from its original version due to its smaller size, but its complexity and probable mixture of materials may require complex and energy intensive solutions in its end-of-life during disassembly and disposal.

c) Designing a robust product that may generate more waste from its consumables and replacement spare parts during its over-extended use phase, than a disposable product.

Therefore, life cycle consideration is important in product design because (Alting et al., 1997):

a) It helps to identify trade-offs of the design to the environmental impact across different life cycle stages.

b) It helps to identify the focus areas in the design that could be improved to reduce the impact.

c) Potential savings can be determined even for the consumers during the use phase, which goes beyond traditional cost accounting for manufacturers.

2.3 Eco-Design in Product Development

According to Graedel and Allenby (1995), the product development process has the strongest influence on the potential environmental impact of a product. However, it greatly varies depending on the product and organization. Given this, there are a variety of approaches used in practice to integrate the environmental impact in product development; therefore a standard method is not feasible. In large organizations where one of the key business strategies would be the enforcement of environmental policies, product development is a formal matter which involves engineers, scientists, suppliers, marketing and management in making decisions and milestones are set to determine if goals are achieved. In smaller organizations which does not have a clear environmental policies (Taha et al., 2010), environmental considerations in product development is seen as an opportunity to improve the design (depending on the designer's sentiments) once the basic customers' requirements are satisfied. Contrasting the two kinds of organization, the former would have a collaborative approach from multiple stakeholders while the latter would be an informal and intuitive process. Whatever the differences are between the two organizations, both have integrated the environmental considerations during product development.

Companies normally have customized product development methods therefore, the priorities on which product development process will they integrate the environmental consideration would be dependent on the company's culture and nature of the product. To fully integrate the environmental considerations in the company's product development processes, they develop their own design standards. One example is Siemens' Standard (SN 36350) which was developed based on the ISO 9000 standard

(Koch, 2000). It is a guideline which covers the aspects of IEC Guide 109 which is specific to the environmental considerations of electro-technical products. The SN 36350 consists of 40 rules addressing all life cycle phases which are integrated into the design process. Key points are:

1. energy consumption during the use phase, particularly for products with long life span
2. reduction and recovery of end-of-life waste
3. substitution of hazardous substances

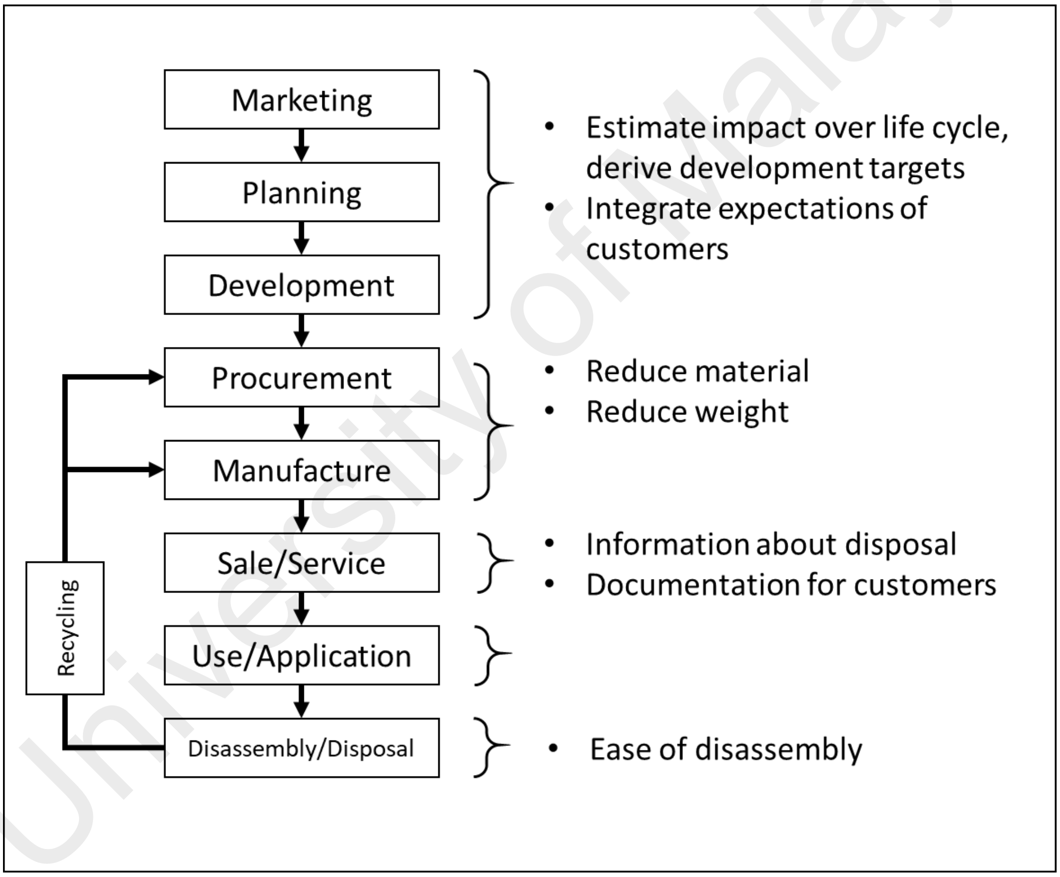


Figure 2.4 A sample of Siemens Standard SN 36350 integration of rules into the design process (Koch)

Early intervention of environmental consideration in design is important because 70-90% of the cost is already determined during research and development. Therefore, higher cost savings could be achieved if the complete life cycle is taken into account in the earlier design stages.

Therefore, eco-design must not be perceived as an additional task to be done by the designer, but rather a paradigm shift and perceive it as a vital step to improve the design by including a broader viewpoint extending to the life cycle to enhance its production, use and end-of life stages. As mentioned previously that organizations would have specific product development processes, they would require specific eco-design tools and methods. The next section discusses some eco-design tools which are categorized according to methods so that it would be easier to differentiate each according to the designer's required information.

2.4 Eco-Design Methods

Eco Design is first and foremost a Product design methodology, and finding the design solution that satisfies the given criteria is its core activity. In the field of eco design, there are several methods developed to aid designers. Many eco-design tools exist ranging from simple to complex; qualitative and quantitative methods and this report categorized these tools according to its use and methodologies.

2.4.1 Guideline based methods – Standards and Handbooks

The guideline based eco design methods covers the product design method by Pahl and Beitz (2007) which starts with problem confrontation, information collection, problem definition, solution creation, evaluation and finally reaching a decision. A set of guidelines are used by the designer which focuses on different attributes across the life cycle of the product. They are developed based on previous levels of knowledge, collected from expert designers with their insights on design methods with the following considerations:

- Use by suppliers;
- Use by small and medium-sized enterprises (SMEs);
- Accommodation of a range of previous environmental and eco-design knowledge;
- Use by a range of functions, management as well as technical;
- Inclusion of specification as well as design considerations;
- Inclusion of management as well as technical considerations.

An international standard for eco design exists in the form of ISO/TR 14062 (Quella & Schmidt, 2002) on Environmental Management - Integrating Environmental Aspects into Product Design and Development. This technical report (TR) covers strategies, organization, planning, tools and the design development scheme for the integration of environmental aspects into the product design and development process. It also includes examples of how to do it and describes the processes, tools and reviews for its integration into ISO 9001 (Quality) and ISO 14001 (Environmental) Management Systems. The ISO/TR 14062 is beneficial for strategic product development because it covers a wide range of management-related activities. However, the tactical design activities may not benefit from it, as products would require specific strategies depending on its product category. Other guidelines are also in the form of standards and/or handbooks which were then further developed to suit product specific requirements. The International Electrotechnical Commission (IEC) published Guide 114 entitled "Environmentally conscious design - Integrating environmental aspects into design and development of electrotechnical products" which is their response to ISO/TR 14062's lack of specific strategies for electrotechnical products (IEC, 2005).

Table 2.1 Example for the application of design rules corresponding to aspects and their consequences over the whole life cycle (Quella & Schmidt)

Life cycle phase	Activities	Result of the Siemens Mobile Phone Base Station BS 241
Marketing, Planning, Conceptual and Detailed Design	Integrate expectations of customers Estimate impact over life cycle Derive development targets like: -reduced energy consumption -reduced hazardous substances	A new cooling (~33% cost) system avoiding an active cooling by air and new patent cooling with membrane filter (= no heat exchanger)
Procurement*, Production*	Reduce material Reduce weight	-New subrack: 1 part/1 material; ca.-80% cost, 25% more space; former rack: 66 parts, 4 materials -Front: pure steel with structured surface, laser inscription, 100% recycling possible
Sales and Service*	Information about disposal Documentation for customers	Service call by software and remote control (= less service cost)
Use/application*	Information about long useful life and product use in environmental favourable way	Power consumption was reduced by ~35%. Sensitivity was increased by +2dB (corresponding power reduction in cellular phones -37%)
Disassembly*, Disposal*	Ease of disassembly	Packaging (now plug 7 play from factory); materials only wood, multi-use Total product: Nearly 100% recycling possible.
**Planning happens during "planning and development phase'*		

2.4.2 Checklist method

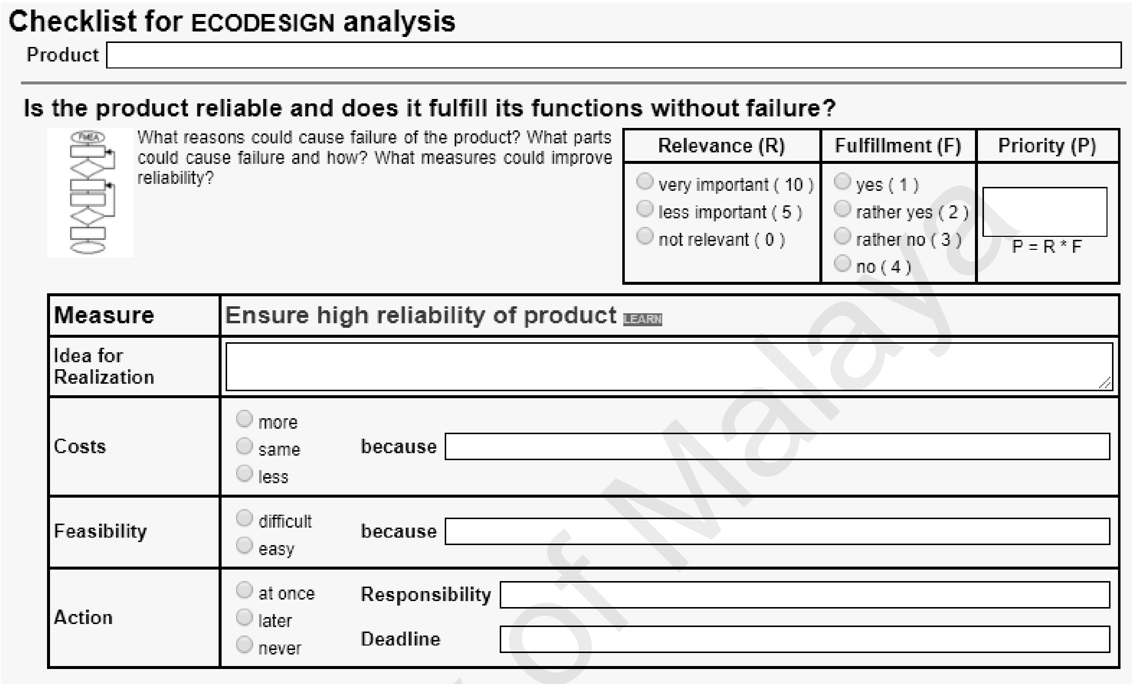
The checklist method employs a tick-list format for designers to respond to particular requirement categories. Responses maybe in the form of YES/NO or ranking according to the degree of accurateness. This method is very popular because it does not require much calculations and detailed analysis on the designer's part especially for companies who could not bear additional work load for the designers. However, this method does not provide a significant result in finding the solution for a product. The Center for Sustainable Design (CfSD) in UK has developed several checklists specifically for SMEs designing EuPs (Energy using Products). One of them is the Eco-design Health check which checks how well the concepts of environmental design are incorporated in the product planning. It is a tool for the very first rough overview of the product, mainly for management assessment purposes. The designer/stakeholder will have to respond to the questions according to its degree of accurateness and the collected points of the responses would generate a decision. The maximum score is 40 and if the resulting score of the checklist is less than 20, then the product needs to have some further action taken immediately. Another checklist developed by CfSD is the Smart ecoDesign Checklist (Clark & Adams, 2002) which provides a more detailed level of analysis. It is intended to ensure that potential environment issues are identified, which serve as basis for making decisions.

Eco-design Health Check						
We design our products to include the following criteria:						
	Environmental Statement	Complete compliance	Partially compliance	Programme for compliance in place	Seldom	Never
	Score	4	3	2	1	0
1.	Minimum use of hazardous materials.	☐	☐	☐	☐	☐
2.	Minimum use of all materials by quantity and number of types.	☐	☐	☐	☐	☐
3.	Minimum use of energy in manufacture.	☐	☐	☐	☐	☐
4.	Minimum consumption of energy while in use.	☐	☐	☐	☐	☐
5.	Minimum need for packaging.	☐	☐	☐	☐	☐
6.	Dismantleable at the end of life.	☐	☐	☐	☐	☐
7.	Recyclable at the end of life.	☐	☐	☐	☐	☐
8.	Measurement and management of production waste.	☐	☐	☐	☐	☐
9.	Suppliers checked for environmental performance.	☐	☐	☐	☐	☐
10.	Environmental benefits to customers continuously improved.	☐	☐	☐	☐	☐
	Sub Totals	0	0	0	0	0
	Total	0 points (maximum score = 40)				Reset

A score of less than 20 indicates that further action should be taken immediately.

Figure 2.5 Eco-design Health Check Checklist

On the other hand, Technische Universität Wien in Austria introduced another approach called ECODESIGN Checklist Method (ECM) (Wimmer, 1999). This uses a series of checklists structured according to the type of product, life cycle and design phase. It aims to identify the design characteristics that influence the environmental performance of the product using qualitative evaluation. An improved version of ECM (also known as ECM version 3) is the Ecodesign PILOT (Product Investigation Learning and Optimization Tool) (Wimmer & Züst, 2003), which has a simplified and optimized structure for ease of use for the designers. Though there is limited information available during the early design stages of the product, specifically its function, structure and materials, this method provides qualitative results quickly; however, the results are dependent greatly on the user's skills.



Checklist for ECODESIGN analysis

Product

Is the product reliable and does it fulfill its functions without failure?

What reasons could cause failure of the product? What parts could cause failure and how? What measures could improve reliability?

Relevance (R)	Fulfillment (F)	Priority (P)
very important (10) less important (5) not relevant (0)	yes (1) rather yes (2) rather no (3) no (4)	P = R * F

Measure	Ensure high reliability of product LEARN
Idea for Realization	
Costs	more same less because
Feasibility	difficult easy because
Action	at once later never Responsibility Deadline

Figure 2.6 Detail of Ecodesign PILOT Checklist

In the eco-design context, design decisions are not only based from technical parameters, but management processes also needs to be considered- like the identification of the variety of functions for the design to ensure early consideration of relevant issues. The checklist methods that were mentioned in this study covered management-related considerations in product design which does not require high technical analysis. Therefore, the checklist method could not be used as a stand-alone tool to determine product modifications or improvement, but is advised to be combined with another eco-design method which focuses on the technical design parameters.

2.4.3 Design for X

During the 1960s, manufacturing companies developed product design guidelines and accumulated them into a reference volume so that designers would be able to acquire the knowledge for efficient design. However, it was observed that the focus of these guidelines emphasized on the manufacturability of individual parts and very minor on assembly processes. Boothroyd and Dewhurst started a series of research on Design for Assembly (DFA) (G. Boothroyd et al., 1983), which considers the assembly constraints such as costs and processes. This research led to the study of several design related fields such as Design for Manufacture (DFM), Design for Manufacturing and Assembly (DFMA), Design for Quality (DFQ), Design for Reliability. The implementation of these design methodologies led to the improvement of products with reduced costs, better quality and faster lead time. More recently, the concerns for the environment have shifted design researches on an environmentally-specific niche, with the more prevalent ones are Design for Environment (DfE), Design for Recycling (DfR), Design for Disassembly (DfD), Design for Life Cycle (DfLC), and Design for Sustainability.

2.4.3.1 Design for Recycling and Disassembly

Recycling has been the number one concern for most manufacturing companies when it comes to reducing the environmental impact because of the fact that the quantity of disposing products has increased dramatically and the spaces to displace them are running out. Furthermore, let's not deny the fact that it has been established that recycling generates profit, of course. However, it has been acknowledged that the disassembly of used products is indispensable in order to make recycling economically viable (Kuo et al., 2001), and should therefore go hand in hand.

Determining the method of disassembly (i.e. by reverse assembly or by brute force) and the sequence of disassembly were the critical issues encountered in DfD. Important considerations are the geometric information (Beasley & Martin, 1993) and material recognition to identify if the assembled parts are necessary to be taken apart (in cases of similar materials assembled together, they may not be needed to be disassembled at all when being recycled). A research trend on the development of indexes to evaluate designs according to disassembly work measurement (Kroll & Carver, 1999; Kroll & Hanft, 1998; Veerakamolmal & Gupta, 1999), disassembly cost and effort (Banda & Zeid, 2006; Das et al., 2000) became popular among design engineers. The eventual integration of DfD and DfR were studied by (Chen, 2001; Ferrer, 2001). Different researchers however moved one notch up and focused on enhancing the disassemblability of a product (Desai & Mital, 2003; Mital & Desai, 2007), which would proactively improve the design of a product using CAD-based approach (Chu et al., 2009) and combined it with optimization methods to solve combinatorial configuration design problems (Kwak et al., 2009; Viswanathan & Allada, 2006). Innovative disassembly methods were also proposed by Willems, et. al. (2005) which involved a disassembly trigger mechanism by subjecting the product to heat, electricity, magnetic, or chemical agents.

It has been proven that it is neither possible nor economical to recycle a product completely so Zussman et.al (1994) proposed three objectives to consider during DfR evaluation: (1) maximize profit over the product's life span; (2) maximize reused parts; (3) minimize weight of landfill waste. Given this, a hierarchy of material's fate after a product's disassembly was developed by Simon (1991) shown on Figure 2.7. This hierarchy means that if more materials invested end up in the higher level, the more source and energy of the product component is conserved. A simple method of quantifying these objectives can be measured by developing metrics and mathematical models. A metric presented by Coulter, et.al (1998) to determine material separation process in early design; and a mathematical model developed by Knight and Sodhi (2000), which evaluates the cost-profit after the product's disassembly and material separation.

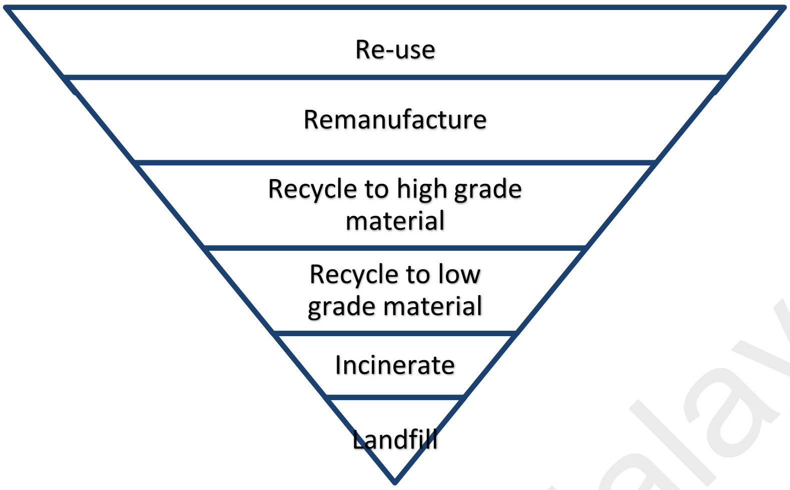


Figure 2.7 Hierarchy of Material destinations after disassembly

In DfD research, one of the obstacles identified that need to be overcome is the problem of product modification during illicit repair which is beyond the scope of a product designer at the moment. An infinite number of possibilities could happen to the product once it reaches the user, which is impossible for the designer to prevent from happening. In addition to this is the wear and tear of joined elements which could be a number of possibilities to cause this. DfR also faces some obstacles in research such as the technology gap of recycling process since the time the product was designed compared to a probable more advanced recycling or re-engineering technology by the time of its end of life. Related to this problem, CIM Institute of Cranfield Institute of Technology conducted research on product evaluation based on the future trends of recycling technology and economy development (Rose & Evans, 1993).

2.4.3.2 Design for Environment

According to Fiksel and Wapman (1994), Design for Environment is the systematic consideration of design issues associated with environmental safety and health during the new production and process development. Its goals are to: (1) minimize the use of non-renewable resources; (2) manage renewable resources; (3) minimize toxic release in the environment. DfE effectively works with the integration of design, database of metrics (i.e. environmental impact) and design optimization (Mizuki et al., 1996). The two important concepts when dealing with DfE is the method of assessing the design and the environmental impact metrics used in the assessment. Some companies develop their own assessment and metrics depending on their specific requirements. Hewlett-Packard, for example, uses a combination of different methods such as DfE guidelines integrated with product assessment and product steward metrics. These tools aid in measuring impacts and define target improvement opportunities useful for optimization and/or decision making.

A trend in devising tools for evaluating product designs with focus on environmental considerations emerged. Feldmann (1999) proposed a metrics called Green Design Advisor (GDA) which collects information from the product (e.g. type of material, toxicity, recyclability, disassembly time). The over-all environmental impact score is obtained by combining all the metrics using multi-value attribute theory. A computer-based tool to evaluate design called ECoDE (Environmental Component Design Evaluation) was developed by Lye et. al. (2002). ECoDE uses Analytical Hierarchy Process (AHP) to rank design criteria and the scores against each criteria are computed for both the component and the over-all product. The resulting component with a large score generated means that this component has less impact on the environment. This is very useful when it comes to deciding on which product or component is essential to be improved. There has been a huge development of design tools that includes environmental considerations since the 1990s and a quick overview of some of these tools is offered by Fraunhofer IZM (2009).

Design for Environment research expanded quickly into several new branches of research which focuses on the impact across the life cycle of a product. These methods have found niches in academia and further enhancement of these methods are widely researched, and deserved to be discussed in their own category of Ecodesign methods. The two most popular methods are Quality-Function Deployment (QFD) based methods and Life Cycle Assessment (LCA) methods.

2.4.4 Quality-Function Deployment (QFD) based methods

Quality-Function Deployment is a method developed by Akao (2004) that translates user demands and functions into product planning and is an established method to achieve customer satisfaction (Bossert, 1991; Clausing, 1994). It is reported that major enterprises like Xerox Kodak, NASA, Motorolla have adopted QFD because of the said benefits (Clausing, 1994; Shillito, 1994). It uses a systematic matrix-based approach following the concepts of Total Quality Management (TQM) which called the House of Quality (HOQ). This basic QFD concept of idea creation in the conceptual design of products is further developed by Cristofari et.al (1996) by integrating this with LCA to evaluate the environmental aspects of products calling it Green QFD (GQFD). Zhang (1999) further extend this model by integrating LCA and Life Cycle Cost (LCC) with QFD into one functional tool which considers customer requirement, cost and environment in the product planning process and called it GQFD-II. In Japan, however a different approach of environmental integration with QFD was developed under the support of JEMAI called Quality Function Deployment for Environment (QFDE) (Masui et al., 2001). This is based from the traditional HOQ and it consists of four phases. Phase

I correlates the Voice of the Customer (VOC) to the Voice of the Environment (VOE) which results in the definition of Engineering Metrics (EM), which will be used in Phase II to be correlated to the Product Characteristics (PC). The results of Phase II allow the designer to identify the significant components of the product that would influence both the environmental and traditional qualities of the product. Phase III and IV are the assessment and selection of the most environmental friendly design among the proposed designs.

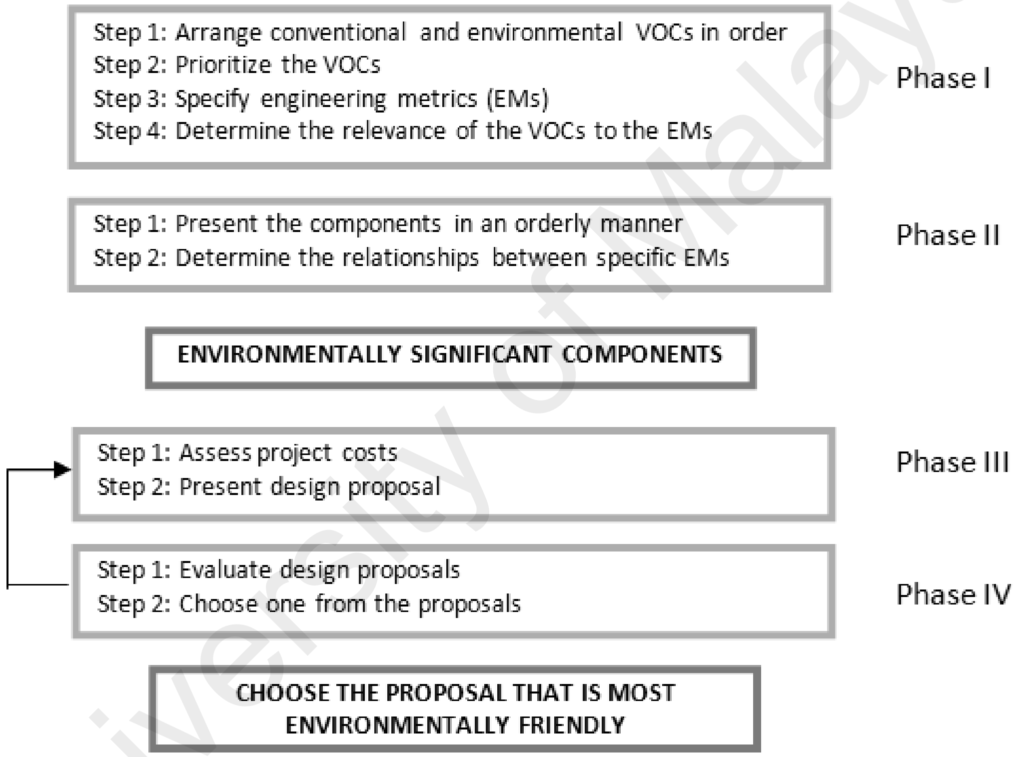


Figure 2.8 Flow of QFDE-based DfE (JEMAI)

One of the disadvantages of this method is obtaining the customer's needs final importance rating values which is a crucial parameter in applying QFD. Typically, AHP is used to derive a conjoint analysis and Chan et. al (1999) developed the integration of customer input using fuzzy logic with entropy methods to successfully maximize the information obtained and reveal the final importance ratings of the customer, however, this requires too much elaborate information from customers regardless of the problem scale and becomes too tedious to come up with a judgment. On the other hand, a straightforward approach using rating systems as in (Green & Srinivasan, 1978) appears to be too subjective and doesn't clearly capture the customer's perceptions. Kuo (2003) developed the Fuzzy-QFD-based method and integrated with LCA to accommodate both customer requirements and environmental impact factors in product planning.

QFD-based methods have been proven to be a reliable method in product development and as mentioned, most companies use this to develop products with high customer satisfaction. However, an existing product must already be in the market to serve as reference in order to gather the customer ratings feedback that is needed to be used in the HoQ tables. Only a limited number of proposed design options for the most environmentally friendly products are available to choose from, though there is no clear basis if the options available could represent the whole design population. There is a danger that the most satisfying and environmental-friendly design could have not been generated and thus not included in the design options to be chosen.

2.4.5 Life Cycle Assessment (LCA) based methods

Life Cycle Assessment is a quantitative eco-design methodology that evaluates the environmental impact associated with products, services, or activities by identifying and quantifying energy and materials used and released to the environment; and to identify and evaluate opportunities to effect environmental improvements (Fava, 1991). The utilization of quantitative data makes LCA a favorable eco-design method because it could give a true measure of environmental performance when combined with indicators like Eco-Indicator (Goedkoop et al., 1998). LCA is also important because it rationalizes the structure of a decision-support mechanism that considers the interaction of both environmental and productivity parameters.

The LCA methodology consists of four phases (Fava, 1991). It begins with *Goal and Scope Definition* which determines the purpose of the assessment and the boundaries of the system. The next step, *Inventory Analysis*, deals with the diligent task of detailing the components involved in the process to quantify resource consumption like raw material, electrical usage and waste generation like pollutants, and solid waste. These are generally represented as an input-output process diagram as shown in Figure 2.9.

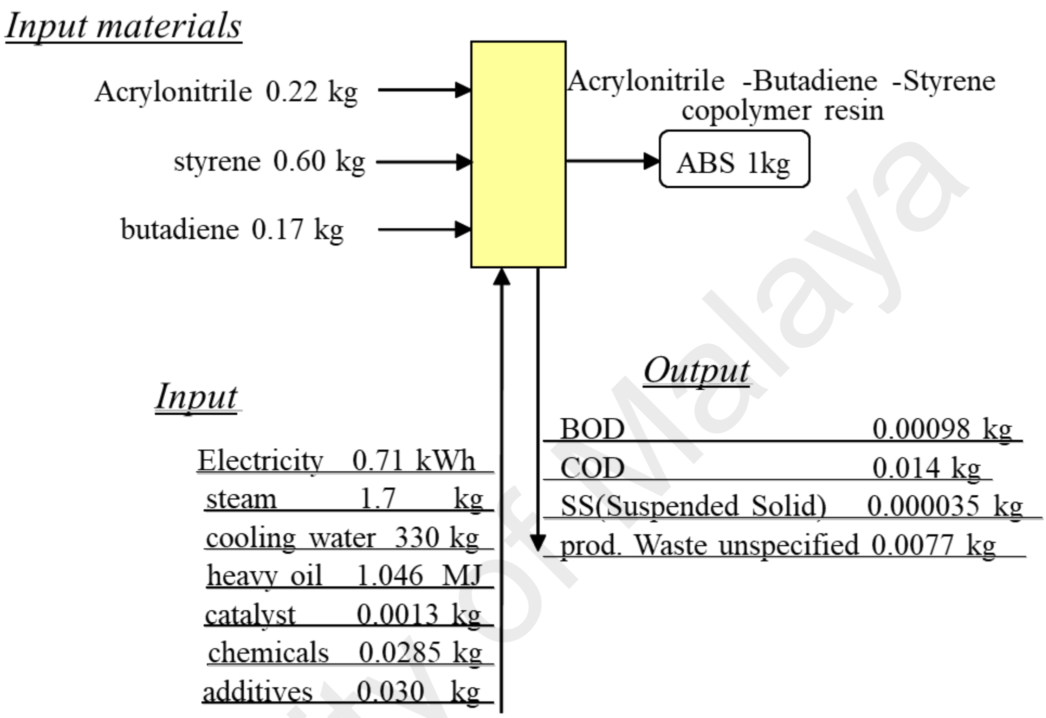


Figure 2.9 Inventory Analysis of ABS plastic

The data from the inventory analysis undergo *Impact Assessment* where they are characterized according to its impact category, for instance, global warming, water resource depletion, and eco-toxicity. This monotonous task is normally easier with the use of LCA software like GaBi, SimaPro and Umberto. A recommended list of selected LCA tools is updated by Garaizar, et.al (Fraunhofer-IZM, 2009). The outcomes of the inventory analysis and impact assessment phases are then summarized in the *Interpretation phase*. It includes the identification of significant factors that contribute to the impacts and providing possible solutions or alternatives to these factors identified. The interpretation phase is a culminating report of the LCA method and presents the final results in a confident, complete and accurate manner by satisfying the initial goals which were presented in the first phase.

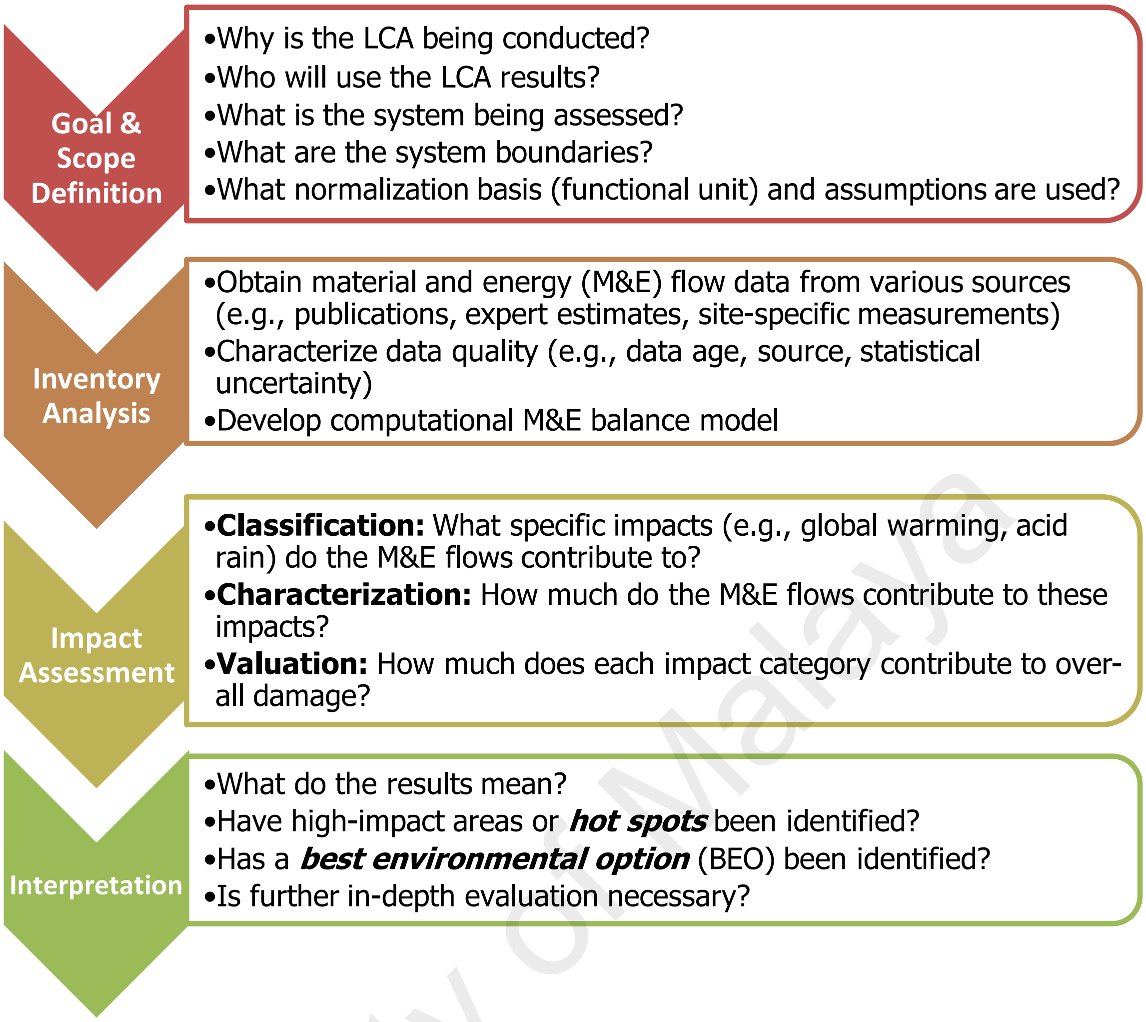


Figure 2.10 Life Cycle Assessment Phases

LCA can be utilized to support different initiatives. During the early days of LCA, Wenzel (2000) have outlined the applications of LCA in terms of its objectives whether be it for Diagnosis or Selection purposes. Several applications were mentioned like Ecolabelling, Community Action Plans, Cleaner Technology, Consumer Information and Product Development. In Diagnosis for Product Development, it is used to provide background for environmental specifications, design strategies, principles and rules. It also supports selection of best choices from alternative solutions.

Despite its variety of applications, LCA is subject to some challenges that hinders its widespread use. First, there is still no standard LCA methodology that is widely accepted. The differences in assumptions of system boundaries and evaluation methods lead to inconsistent results. It may be considered irrelevant to compare the environmental impact reductions of products from competing companies unless they are interpreted using the same assumptions or are verified by the same third party certification agency. Second, LCA is heavily dependent on data. Impacts are assessed using data which are gathered from variable resources publicly available from scientific journals, government agencies and such. There is no standard that governs the quality of these data, and combining them to form datasets could result in indiscrepancies due to the differences in assumptions, which was also mentioned previously.

2.4.5.1 Specific Energy Consumption (SEC)

An important research that needs to be mentioned in this review, specifically in the assessment of impact during the manufacturing stage, is the research conducted by Gutowski and Dahmus, which focuses on the Specific Energy Consumption of different manufacturing processes. The assessment of the energy consumption of the machining process (Dahmus & Gutowski, 2004) is based on the different parts of the machine that requires power, for example, Coolant pump, Servo motors, etc. The study was able to determine which power-consuming devices are dependent on the machining time, and which are independent. This was used as the basis for determining how much energy is used per material removed. Different factors are also considered, such as the type of material being machined as the basis for the assumption used in determining the material removal rate. With specific assumptions and power measurements, the study was able to generate energy analyses on different kinds of machines. There are different SECs for each machine type, because it is dependent on its power profile.

Table 2.2 : Energy analysis for two different kinds of milling machine

	Production Machining Center (2000)		Automated Milling Machine (1998)	
Energy Breakdown				
Constant start-up operations (idle)	85.2%		13.2%	
Run-time operations (positioning, loading, etc)	3.5%		20.2%	
Material removal operations (in cut)	11.3%		65.8%	
Energy Requirements				
Constant start-up operations (idle)	166 kW		1.2 kW	
Run-time operations (positioning, loading, etc)	6.8 kW		1.8 kW	
Material removal operations (in cut)	22 kW		5.8 kW	
Machine Use Scenario				
Arbitrary Number of work hours	1000 hours		1000 hours	
Machine uptime	90%		90%	
Machine hours (idle, positioning, or in cut)	900 hours		900 hours	
Percentage of machine hours spent idle	10%		35%	
Machine hours spent idle	90 hours		315 hours	
Active machine hours per 1000 work hours	810 hours		585 hours	
Machining Scenario				
Percentage of machine hours spent positioning	30%		60%	
Machine hours spent positioning	243 hours		351 hours	
Percentage of machine hours spent in cut	70%		40%	
Machine hours spent in cut	567 hours		234 hours	
Energy Use per 1000 work hours				
Constant start-up operations (idle)	149288 kWh		1038 kWh	
Run-time operations (positioning, loading, etc)	5471 kWh		1033 kWh	
Material removal operations (in cut)	6237 kWh		673 kWh	
Total energy use per 1000 work hours	160996 kWh		2744 kWh	
Energy Used per Material Removed				
Material Machined	Aluminum	Steel	Aluminum	Steel
Material Removal Rate	20.0 cm^3/sec	4.7 cm^3/sec	5.0 cm^3/sec	1.2 cm^3/sec
Material removed per 1000 work hours	40824000 cm^3	9593640 cm^3	4212000 cm^3	1010880 cm^3
Energy used/Material removed	**14.2 kJ/cm^3**	**60 kJ/cm^3**	**2.3 kJ/cm^3**	**10 kJ/cm^3**

2.4.6 CAD-based Integrated methods

As mentioned in the motivation from chapter 1, integrated methods could potentially yield greater environmental impact reduction. Ishii and Hornberger (1992) also mentioned that for a tool to have a long term value, it must have a focused specialization with simple input and output of data. It is important to note that this section of the literature review is focused on the integration of Eco-design with the tool widely used by Product Designers, which is the Computer-Aided Design software, or CAD. The integration of eco-design strategies with CAD promotes interlaced methods, which provides seamless transition from one process and/or method to another. This approach generally starts with the assessment of a completed CAD model. Assessment of the product design is the first step to determine the amount of impact for a specific design. This section focuses on the different methods assessing the potential environmental impact of a design based on CAD information. Some assessment methods used are based from the previous methods discussed in the previous sections, but it is important to note how the design is translated into assessments.

Friedrich and Krasowski (1998) and Hato (1998) have tried to integrate the LCA process into a CAD/CAM system and apply LCA to industrial products. However, the environmental impact could not be understood immediately from the CAD/CAM data because the CAD design process remained completely independent of the LCA process.

The breakthrough in LCA-CAD integration was inspired from the proposed integration of CAD models with LCA by Otto & Kimura (2003), which uses feature technology as a means of extracting design information. Information gathered such as the type of material, the manufacturing method, and surface finish is important to generate the manufacturing scenario. It also employs the use of databases for storing LCI information. A module application programming interface (MAPI) is developed to allow the possibility of changing the set of design features and its properties (i.e. type of material). The result is to be able to generate a Life Cycle Analysis from varying material options, and manufacturing processes. The results from the research seems promising, however the line of their research did not further lead to this direction.

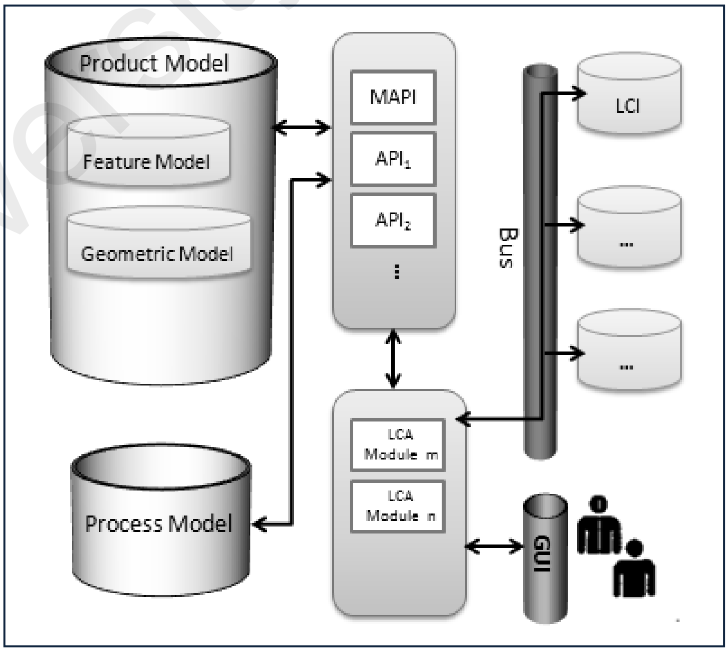


Figure 2.11 Architecture and Components of Otto and Kimura's Integrated CAD and LCA method

To address the needs of the designers with regards to further actions after the LCA information have been retrieved from their CAD designs, Capelli, et. al (2006) proposed the further development of the integrated CAD-LCA systems with the addition of Eco-design guidelines as feedback. The system generates an accurate Abridged Life Cycle Assessment (aLCA) from the CAD information. With this, the designer can immediately identify which components have a high environmental impact and can modify them accordingly. As shown in Figure 2.12, the modification of the designs is executed during the Concept, Product and Engineering Design phases. The designer is aided during these modifications by the interaction of the three databases: Guidelines, LCA and CAD features. However, this would also require maintenance of these databases in order to suggest a strong sub-set of alternative eco-design solutions.

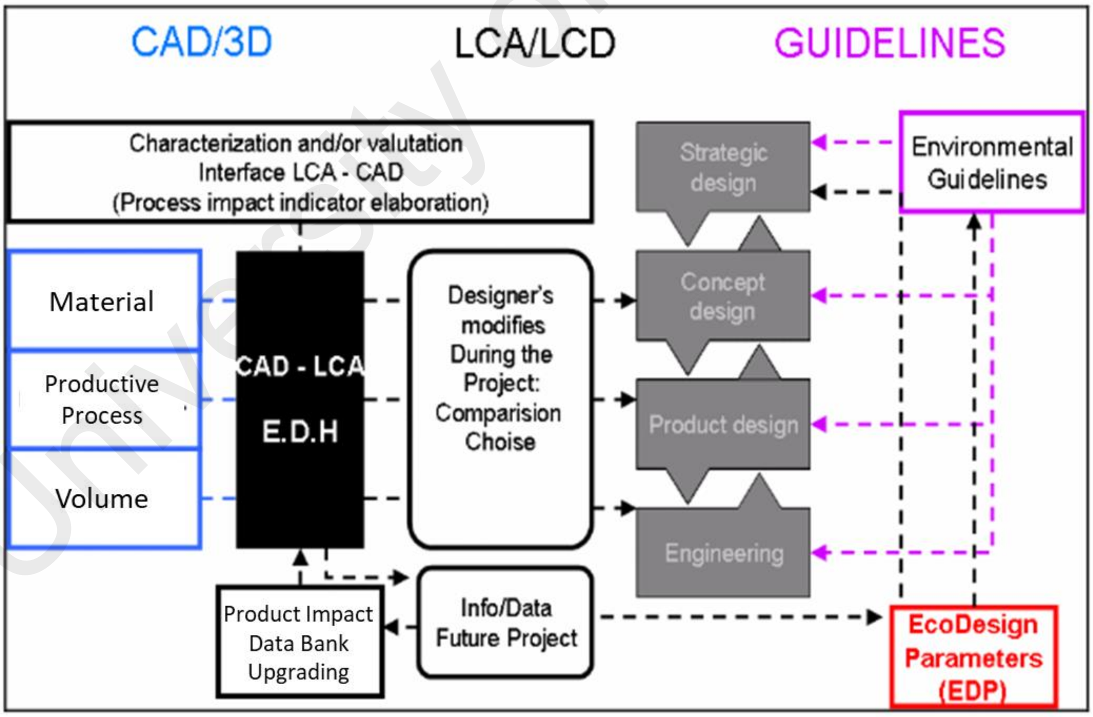


Figure 2.12 Schematic view of LCA and Guidelines integration in 3D CAD model (Cappelli, et al.)

Solidworks CAD software has released their Sustainability Xpress module, which integrates the product design in CAD with the GaBi LCA software. It is a quick analysis tool which automatically calculates the potential environmental impact across the life cycle of the product according to its material composition, manufacturing process, and intended location of its usage and disposal. It also provides a comparison report of the impact based on the design changes. The impact assessment of the manufacturing stage is computed based on the volume of the product multiplied by the impact factor of the process per cubic cm based on the GaBi LCA software.

Looking deeper into the Manufacturing aspect of the Environmental Impact Assessment of designs, conventional analysis systems evaluate the impact on the differences of dry, wet, and semi-dry machining. However, these systems do not consider the cutting conditions and the volume of material removed, which are significant contributors to the environmental impact. Nawata and Aoyama (2001) has suggested the use of LCI data and linked it to the CAD/CAM data as shown in Figure 2.14. CAD/CAM data contains not only the form features but also the machining features, which calculates the volume of material removed and machining time respectively. Power and Coolant consumption are then calculated which lead to the amount of environmental impact of the design specific to the manufacturing process. The study was also able to compare the impact of the 2 different kinds of material cooling methods, which are the conventional cooling system and the modified minimum quantity lubrication (MQL) system. The resulting consumption data is translated into kg-CO_2 equivalent, which makes it possible to have a straight forward comparison to other process, or as a supplement to the whole Life Cycle Analysis.

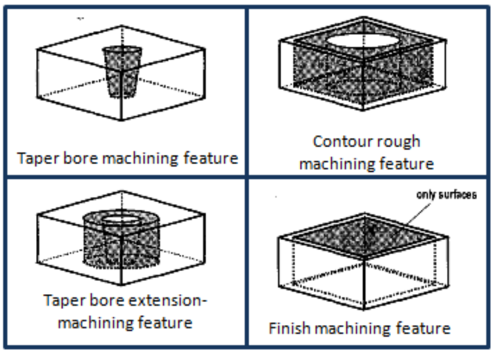


Figure 2.13 Machining features

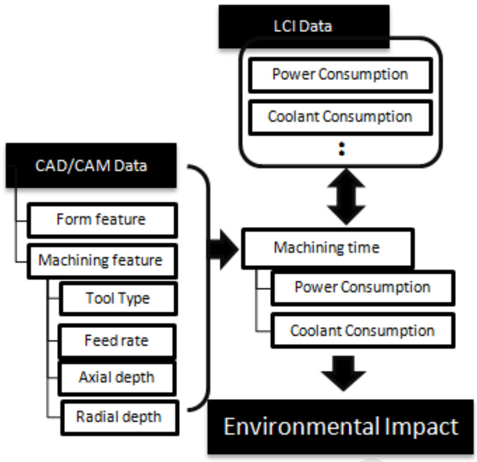


Figure 2.14 Linkage of LCI data to CAD/CAM data

In a similar research conducted by Narita and Fujimoto (2008) which also focuses on the machining operation, they developed an environmental burden analyzer specifically for the machine tool operations. In comparison to Aoyama's research, both methods use product information to extract the machining scenario which is used to calculate the amount of coolant and lubricant consumption, as well as the amount of material (to be) removed. The difference lies in the extent of the boundary of the analysis, where it also includes the analysis of the cutting tool. The source of the product information also differs as Aoyama used feature technology, while Narita used NC data to compute the machining scenario. The end result also shows the comparison of the environmental burden (impact) of several machining scenarios.

The aforementioned researches apply to some extent Life Cycle Analysis in the assessment of the environmental impact. They focus on material reduction, energy and resource consumption, cutting fluid application and waste management. However, the issues with regards to sustainability, which covers the Economic, Environmental, and Social aspects, are not analyzed. The complexity of assessing the social impact of manufacturing requires information from the manufacturing plant's working environment and possibly the occupational health history of the workers. A particular research conducted by the group of Lu, Rotella et. al. (2011) applied a metrics-based sustainability assessment, which covers the elements of design for sustainability, on a drilling process. The study compared the assessment values of a 90mm deep hole drilling process to an optimized drilling process with focus on tool geometry and process parameters. The assessment is presented in scale form from 0 to 100, which the deterministic elements including cost, energy consumption and waste management are normalized. However, for the non-deterministic elements including environmental impact, operator safety and personnel health, the score is given based on the better or worse scenario. The better case is given a 100% score and the score of the worse case is given proportionally to the actual value.

Table 2.3 Example of process metrics for sustainable machining (Lu, et al.)

Environmental Impact	Energy Consumption	Cost
GHG emission from energy consumption of the line (ton CO_2 eq.) Ratio of renewable energy used (%) Total water consumption (ton) Mass of restricted disposals (kg) Noise level outside the factory (dB)	In-line energy consumption (kWh) Energy consumption on maintaining facility environment (kWh) Energy consumption for transportation into/out of the line (kWh) Ratio of use of renewable energy (%)	Labor cost ($) Cost for use of energy ($) Cost of consumables ($) Maintenance cost ($) Cost of by-product treatment ($) Indirect labor cost ($)
Operator Safety	**Personal Health**	**Waste Management**
Exposure to Corrosive/toxic chemicals (incidents/person) Exposure to high energy components (incidents/person) Injury rate (injuries)	Chemical contamination of working environment (mg/m^3) Mist/dust level (mg/m^3) Noise level inside factory (dB) Physical load index (dimensionless) Health-related absenteeism rate (%)	Mass of disposed consumables (kg) Consumables reuse ratio (%) Mass of mist generation (kg) Mass of disposed chips and scraps (kg) Ratio of recycled chips and scraps (%)

2.5 Literature Analysis of Eco-Design Methods

Most of the methods discussed in section 2.4 all approach the reduction of environmental impacts but with varying criteria and stage of application. Various focal points concerning strategic product development, customer requirements and suitability of the method are the primary reasons in choosing a specific eco-design tool. Below is a brief summary of the eco-design methods discussed with their corresponding strengths and weaknesses based on the previous sections.

Table 2.4 Summary of Eco-design methods and tools

Eco-design Tool	Design Stage applied	Advantages	Disadvantages
Guidelines - ISO/TR 14062 -IEC Guide 114	Strategic Product Development	-methodical process of problem identification and finding general solutions	-tactical product design does not benefit from it because products require specific strategies depending on its category. -lack of explanation of concrete methods for solution
Checklist method -Ecodesign Checklist -Ecodesign PILOT	Strategic Product Development (Management)	-ease of use because of its low load to users and does not require much effort from designers	-does not provide concrete solutions to aid designers in product improvement -reliance on qualitative analysis and low transparency of the process of identifying solutions
Design for X	Various, mainly in the Concept and Detailed Design	-deals with specific issues within design, ie: recyclability of the product, etc.	- may have problems integrating with other X issues. ie: finding weights for decision-making
Quality-Function Deployment (QFD) based methods	Concept Design	-translate the customer requirements and environmental considerations into product attributes -support in concept generation	-a first generation product is required to gather customer's feedback -danger of not generating the best design solution
LCA	Various, but generally for Selection and Diagnosis purposes.	-quantitative and objective data	-requires much effort in data collection -will work only after the development of first generation product
CAD-based Integrated Methods	Detailed Design	-Quick assessment result -Less effort on the part of the designer as this is already integrated with existing work	-Assessment does not represent the true effect of design to the manufacturing process

Energy consumption is the most analyzed impact in the research works reviewed. The research conducted by Dahmus and Gutowski (2004; 2006) is particularly interesting because it focuses on the assessment of the energy consumption of the machining process which is similar to the objective of this research. It provides a factual estimate of the energy consumption because it considers two important factors: The measured power profile of the machine and the material cutting rate which is dependent on the type of material being machined. It is believed that this method can be further developed by generating a more detailed estimate of energy consumption by analyzing the design of the product, and be able to identify the different material cutting rate in specific product designs. Given the machining standards formula, one can predict the estimated cutting rate and time for specific product features.

Comprehensive environmental impact assessments integrated with CAD are widely researched. Furthermore, the integrated methodology proposed by Otto and Kimura (2003) uses the feature technology efficiently as input for the product design assessment. It seems to be a promising method with several possibilities for other values besides the Environmental Impact, like Life Cycle Costing, Disassembly/re-assembly related to material recycling and refurbishing can be computed. That is why in a recent publication in 2012 by their co-author, Germani (2011), they proposed to develop a GUI software to integrate CAD, PLM and LCA softwares, and still uses feature technology as a key information input. Though this method results to an LCA of the product design, it is still lacking feedback to the user, and therefore, it is still up to the user's own discernment of the resulting LCA analysis on what to do with regards to the improvement of the product design. Similarly, the Solidworks Sustainability Xpress also supports the environmental impact assessment of the product and generates a comparative report of impact based on design changes. It is a quick and easy analysis but also using a straightforward computation by multiplying the product volume with the constant determined by the GaBi LCA software based on the values of the given manufacturing scenario. Despite its ease of use, the software does not provide a rational assessment, particularly on its manufacturing stage. An in-depth look at this particular issue is discussed on Chapter 5.

On the other hand, the research conducted by Aoyama and Nawata (2001) uses machining features as assessment parameters but only considers Power and Coolant consumption as environmental impact, while as Fujimoto extended it with the inclusion of Lubricant consumption, tool life and waste generation. The beauty of the Aoyama and Nawata research is that they used the standard value of kg CO_2-equiv as a result of their assessment. However, both researches focus on improving the impact directly on the manufacturing process and the results does not lead to a change in the product design. The focus of improvements was on manufacturing processes like lubricant delivery system, such as the use of Minimum Quantity Lubricant (MQL) and tool life improvement.

A complete sustainability assessment of the manufacturing process involves an interdisciplinary research together with occupational health and safety. This would require an intensive amount of the workers' health data to be collected through the span of his/her work. The approach by Lu, et.al. (2011) (2011) leaves many questions open as the quantification of the health and safety of the operators are considered as non-deterministic elements and thus evidence of improvement with respect to these parameters is not realized.

All of the methods discussed do not provide a direct feedback based on the generated assessment. A feedback to the design which would improve it to a more optimum one will reduce the designer's tasks of environmental impact analysis. Using optimization methods integrated with design assessments makes it achievable. The succeeding section discusses the possible intelligent approaches that can be integrated with eco-design methods to generate a design improvement feedback.

2.6 Intelligent Approach to Product Design Optimization

Most designers still optimize engineering designs by doing an iterative procedure of comparing few designs, limiting their designs according to the constraints, and selecting the best design based on the given criteria. This common procedure is normally not published, but practiced in the industry. It limits the outcome of a probably better design, in case the designer does not come up with the optimum design in the first place. Such ”expert-based” approaches use knowledge-based judgment together with simulation tools such FEA or CFD, which depends on the few experts who can truly find novel designs based on the analysis.

Combinatorial optimization problems such as in product design are still difficult to solve. If the design factors of a product, say for example in a coffee maker: the body size, material, filter and heating element, would have three different levels each for these factors (i.e. material could have a plastic, aluminum, or stainless steel configuration), then it would result in 81 ($3^4 = 81$) design options to be considered! And with the addition of another more factor and level for each easily results to 1024 combinations! Searching for the optimal solution of such large-scale class problems by going through each design option is impractical. Luckily, heuristic methods like Design of Experiments, and algorithm-based methods have been developed to find the solutions to these problems without the potential tedious work.

2.6.1 Design of Experiments

Design of Experiments (DOE) is a method to observe the effect of certain parameters to the system given the changes in the design factors. A relationship between the input (design factors) and output parameters (design criteria i.e. cost, product volume, etc.) is established through actual experimentation or simulation based on an orthogonal array configuration. Once the relationship is identified, this information is used to derive the design variables that are expected to yield the best result.

In product design, the traditional full factorial configuration, which involves extensive design scenarios using all the values within the design factor limits, proves to be a very manual and tedious process amounting exponentially according to the number of factors and their levels. Filtering designs introduced by Genichi Taguchi replaced full factorial configurations with a fraction of the design scenarios (Pavlik, 2012) by reducing the accuracy of the interaction among the main factors. Usually, this method consists of 8, 16 or 27 separate orthogonal arrays depending on the number of design factors to be optimized. For example, if you have a design with seven factors, developing designs each with their minimum and maximum values using the full factorial configuration requires 128 designs. On the other hand, using the Taguchi method reduces the design options down to 32. Then, a signal to noise ratio (S/N ratio) value is calculated for each design scenario, which is statistically analyzed using ANOVA techniques. To maximize the design's criteria satisfaction and minimize the noise, factor levels with the highest impact are selected as the optimum design variable values. This greatly reduces assessment and analysis time for all the designs. According to Roy (2008), designers can find better performing designs that are outside their "comfort zones" using the DOE approach. It works fairly well with design variables that are independent with each other but in real life situation that is not always the case like in (Khoei et al., 2002; Madu & Madu, 1999)

2.6.2 Algorithm-based Optimization methods

With the research on algorithm-based optimization alone, there are several methods developed which would be suitable for specific problems. These algorithm-based methods can be sub-divided into general categories according to the properties of the problem to be solved. In this research which deals with engineering design, the focus of the study deals with the multi-objective problem category, which aspires to optimize multiple design parameters. The succeeding section discusses some multi-objective optimization methods which have been widely used and/or studied in Product Design according to the Engineering Village Database (Rajkumar Roy, et al., 2008).

2.6.2.1 Goal Programming (Linear Programming)

Goal Programming (GP) is a type of multi-objective optimization method which converges towards several objectives (goals) simultaneously. It searches for possible design configurations that would satisfy the objectives within the defined limitations and constraints in the search space. This method uses linear programming as a search technique, where a starting point is selected. From this point, the non-linear model and constraints are linearized to obtain a linear problem, which can be solved using the Simplex Method. The point from the linear programming solution can be used as a new point to linearize the non-linear problem, and this iterates until the point where the objectives are satisfied is found. The sequential approach makes this method particularly successful in topology/shape and building layout designs as in (Bhowmik, 2007; Etman et al., 1996; Yang & Chuang, 1994).

2.6.2.2 Simulated Annealing

Simulated Annealing (SA) originated from the annealing process of metal, heating it to a high temperature and slowly cooling it until the desired grain boundary configurations of the metal are obtained. SA starts with an initial given solution. The “temperature” is systematically increased to search for neighboring solutions to the current initial solution. Then comes to a point where a comparison of the values of the objective functions between the two solutions happen. If the neighboring solution has a better value than the initial solution, then it becomes the current solution. If the neighboring solution has a worse value otherwise, then the initial solution retains its position as the current solution. This iterative process of neighbor search and comparison is repeated until a stopping criterion is met. This probabilistic approach has been successfully applied to manufacturing cell design and development of optimal product assembly sequences as in (Benvenuto et al., 1992; Milner et al., 1994; Su & Chang, 2000).

2.6.2.3 Genetic Algorithm

Genetic Algorithm (GA) use biological methods such as reproduction, crossover and mutation to search for solutions to optimization problems. Sets of random values called *chromosomes*, which are represented as a string of bits or characters called a *gene*, are initiated at the start of the method. These chromosomes are then assessed to identify if they would be the “fittest” among them. These fit chromosomes are then carried over to the next generation, which means they are saved, and interact with each other through reproduction. They can reproduce a new set of solutions using either crossover or mutation method. Crossover involves the exchange of random genes between two chromosomes to produce two new different chromosomes. Mutation on the other hand, randomly alters the gene to produce a new chromosome. These newly produced chromosomes are the new generation and they undergo the same fitness assessment to select the new “fit” chromosomes that are to reproduce. The methods of mutation and crossover repeat until a terminating criterion is met. GA is the most widely researched method for product design optimization because of its combinatorial nature. In research, it enjoyed success specifically in the field of design parameter optimization, shape optimization and topology optimization as discussed in (Coello et al., 2007; Deb, 2001; Pham & Karaboga, 2000; Rajkumar Roy, et al., 2008).

A variation of GA, NSGA-II, is multi-objective optimization algorithm based on non-dominated sorting. At first offspring population is created by using the parent population. The two populations are combined together to form population of size 2N. Then a non–dominated sorting is used to classify the entire population. After that the new population is filled by solutions of different fronts, one at a time. The filling starts with the best non-dominated front and continues with solutions from other fronts until the population size of N is reached.

2.6.2.4 Genetic algorithms for design optimization

GAs in product design are mostly used for design parameter (size) optimization, and shape optimization.

2.6.2.5 Parameter Optimization

Problems include automotive design of parts like chassis, turbine blade cooling system, bearing design, and composite drive shaft. Most of these applications are multi-objective in nature with less than 5 objectives and minimum constraints (Antonio, L. M., & Coello, C. A. C., 2017). One of the challenges of parameter optimization is to deal with design variable interaction, and the relationship of the fitness functions, and their degrees of inseparability as showcased by (Roy, et. al., 2003). This relationship is difficult to obtain analytically, and even if it is found, it has limited usefulness since mapping from function space to variable space is very complex. The existence of a relationship among the decision variables of these solutions. An advanced GA called generalised regression GA is used to explore this relationship. It can handle complex inseparable function interaction to identify a range of optimum feasible designs from which one could finally be chosen based on designer's preference.

Another challenge in parameter optimization is the computational cost of the fitness functions. In the trend of literature, multi-optimization problems use a hybrid genetic algorithm solution, where the algorithm identifies good solutions, and then a local search to find the optimum solution (Yepes, V., et.al., 2017), (De Paula Garcia, R., et.al., 2017), (Yun, Y., Jo, J., & Gen, M. (2017). Because multi-objective optimization deals with a small number of objectives, the handling speed is improved with the fitness assignment stage of the GA, and are based on a "Constraint-first-objective-next" model. According to the observations by (Roy, et.al., 2008), design problems with more than 10 design variables are often expensive to evaluate. One approach to reduce the cost is to use meta-models instead of simulation-based models. (Baklacioglu, T., et.al., 2015) created an inexpensive model of the design using neural networks. The model development requires more example design solutions than fractional factorial designs, like Guassian process regression. (Mukhtar, A., et.al., 2017) showed a kriging assisted multi-objective GA where Gaussian process regression based meta-model is used to evaluate some designs. If this evaluation changes the non-dominated solution within a GA generation, then those designs are evaluated using simulation. This method reduces the overall number of evaluations required and is suitable for expensive design problems.

Another type of hybrid GA is integrating local search techniques, only at the end of the GA, and is suitable for multi-level design problems. (Luo, L., & Dai, L. 2005) presented a hybrid GA that incorporates previous knowledge about the design, which improves the quality of the initial population, which would provide better genetic elements for the next generations.

2.6.2.6 Shape Optimization

Shape optimization has a large number of variables and expensive evaluation. Design applications include compressor blade profile, haptic devices, pole shape of the synchronous generators, and nozzle shape, and free form surfaces. Hybrid GA is also popular in shape optimization problems, but due to the relatively larger number of design variables, their degrees of freedom also increases. The expensive computation of the optimization is dealt through the integration of game theory as presented by (Lee, D., et.al., 2011), (Shi, Y., et.al., 2014) or by more efficient GAs that require less expensive design evaluation.

2.7 Theoretical Framework

In the preceding chapter, the need for research in the field of eco-design has been made clear. The literature review discusses the different approaches of eco-design available and has identified the strengths and weaknesses of these approaches, which can be analyzed as possible research gaps. This section points out the identified research gaps and combines these with the research motivations to come up with a research proposition.

2.7.1 Research gaps

There are a variety of eco-design tools available, but lacks a systematic approach as a whole. The eco-design strategies presented mainly deals with scoring and assessment of environmental impact. Based on the analysis of literature, the following points are identified as research gaps:

1. Current available methods primarily deal with problem identification which focuses on which area needs to be improved, but with minimum concrete solutions. The design solutions presented may not be tangible to designers, especially if the solution presented is qualitative.

2. Solutions offered do not feedback directly to the design of the product. i.e.: Process Optimization, Packaging Redesign, etc.

3. In the Integrated CAD+LCA approach, the machining parameters were not considered, which would not be representative of the potential impact of machining processes

2.7.2 Theoretical Framework of the Research

Figure 2.15 presents the overview of the theoretical framework of the research. It connects the motivation to justify the need to conduct this research, to the research gaps identified and the proposed solutions to seal these gaps. The purple boxes represent the main body of the research. From the design of the product, with its proper impact assessment, results to the identification of the design parameters that can be possibly improved. These identified design parameters are sent back to the design as feedback, which eventually lead to a reduced potential impact. The motivations are in green boxes and the research gaps are in red boxes. A further discussion of their connections is continued in the succeeding paragraphs, with the motivations and research gaps underlined.

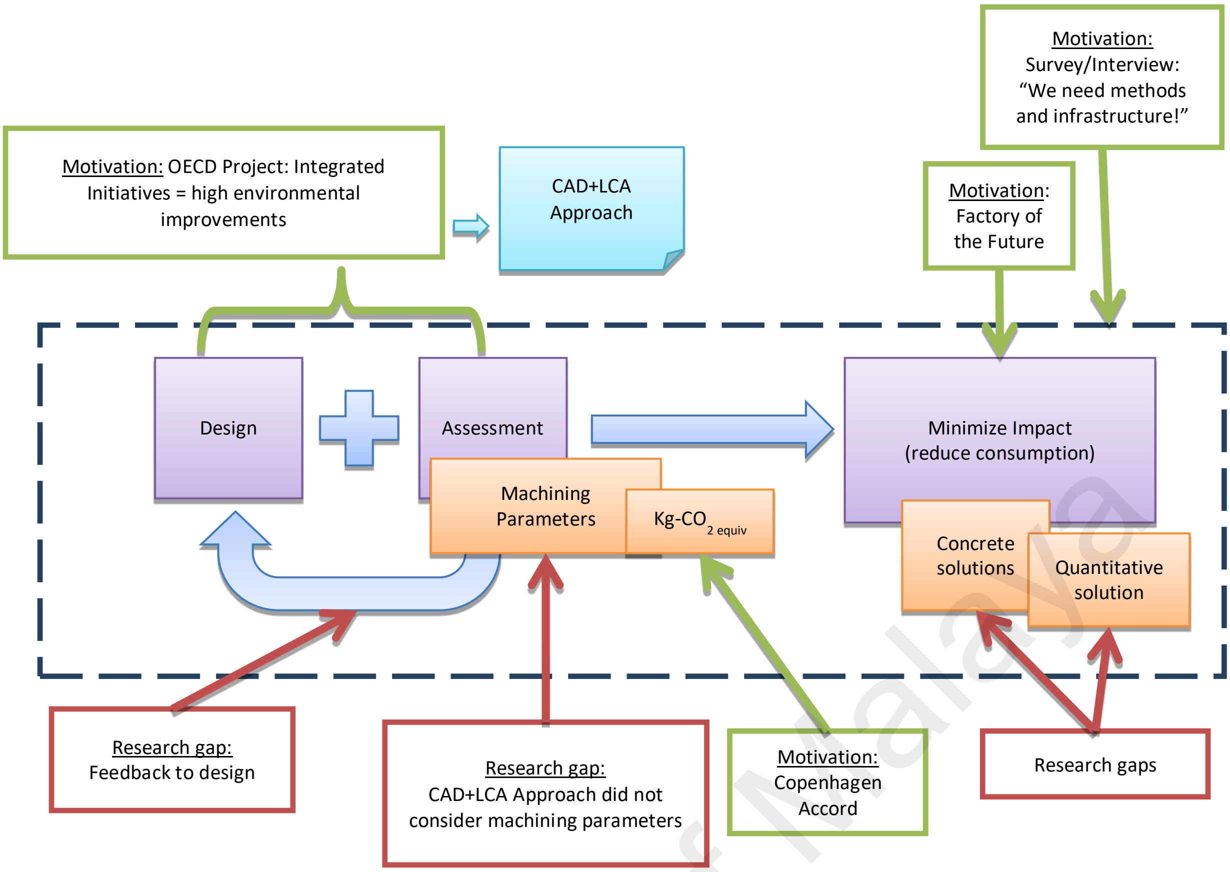


Figure 2.15 Overview of the Research Framework and their relationship to the research gaps and motivations

According to the OECD Project on Sustainable Manufacturing and Eco-Innovation, there is a call for research on integrated initiatives for multi-level eco-innovation which can yield higher environmental improvements. This kind of research usually deals with the integration of existing methods which aims to reduce tasks by reducing the number of steps or processes for the worker, and also to reduce data handling problems and data incompatibilities. Among the Eco-design methods reviewed, the CAD+LCA Approach heeds the call of integrated initiatives. It provides a seamless flow of information that the designer provides in CAD software, and is then translated into useful environmental information in terms of CO_2-kg equivalent (to correspond with the Copenhagen Accord implementation), which can be used in design assessment. However, the current CAD+LCA approach does not represent the true relationship of design and the manufacturing process in terms of its environmental impact, as stated in section 2.4.6.

This research focuses on the gap in the current research which shows that machining parameters are not yet considered in the assessment and the inclusion of these would provide a more realistic assessment of the environmental impact of the machining process of a specific product design.

According to the Factory of the Future (EU-Commission, 2010), research should also focus on the reduction of environmental impact, however, concrete solutions to design improvement is still lacking in current eco-design research. The next step after identifying areas for design improvement is to propose design solutions to these areas. These proposed solutions can then be fedback directly to the design after the assessment, which provides a quick response to the design process. This can be achieved by deriving concrete or quantitative design solutions by using optimization methods with the environmental impact as a primary parameter.

And lastly, according to the conducted surveys and interviews, a method is needed in order to achieve this. Designers do not have environmental impact assessment knowledge/training which they would need to improve the design. However, if this method can be packaged together as an integrated method/tool to their current design methods/software, then this would be aid them in integrating environmental concerns in their designs.

2.8 Chapter Summary

This chapter provided a clear picture of the sustainable manufacturing methods and why design plays a vital role in the improvement of the environmental impact of a product. Also, this chapter discussed the different eco-design and intelligent product design optimization methods and criticized its strengths and weaknesses. This led to the identification of the research gaps and to the development of a general theoretical framework for the research. The following chapter details the research methodology used to address the identified research gaps to be focused.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The aim of this chapter is to explain the research approaches to be used in order to satisfy the objectives established in chapter 1. The flow of the research activity starts from devising the research framework until the validation of experiment results. By conducting literature review and gathering information about the (lack of) eco-design practices of local Malaysian designers through surveys and interviews, the gaps in research were identified. This leads to the development of the theoretical framework. This framework is the basis of the eco-design methodology that will be developed to aid designers in evaluating the environmental impact and optimizing their designs. The justification of methodologies used in this research and other subsequent activities to achieve the research goals are also discussed here.

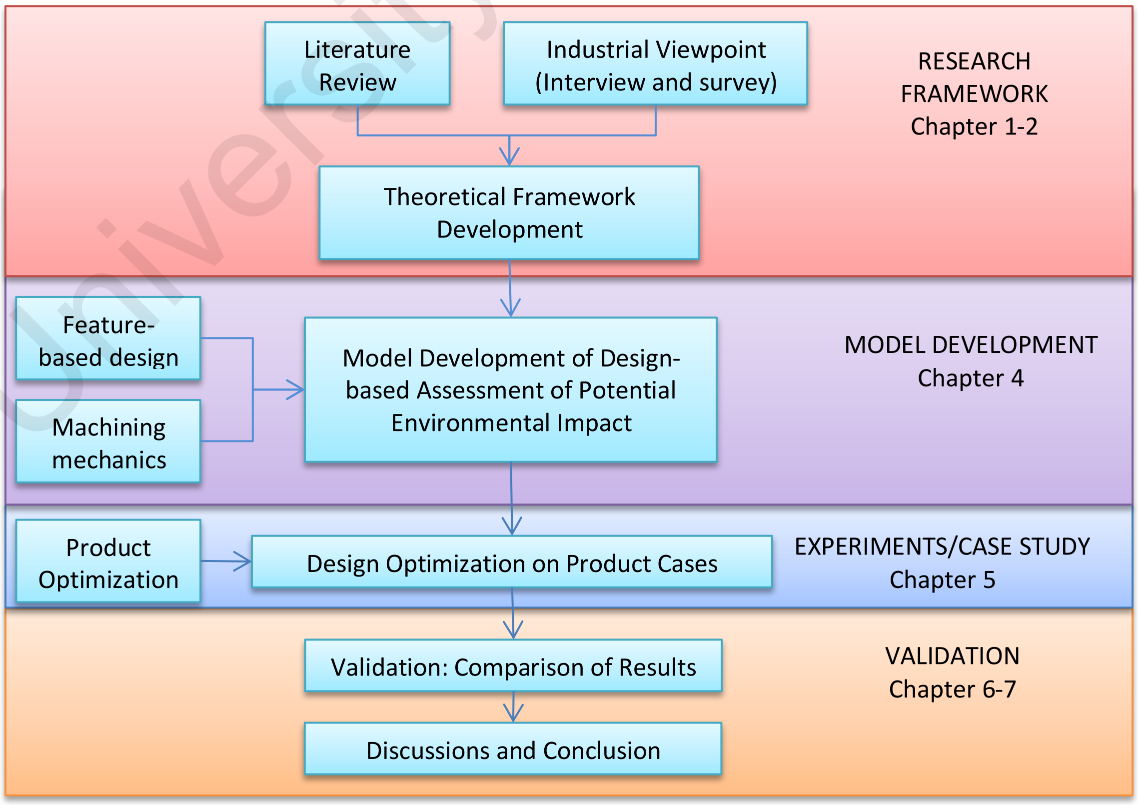


Figure 3.1 Research Methodology Framework

3.2 Research Strategy

The Sustainable Manufacturing Research Group of the Center for Product Design and Manufacture at University of Malaya has developed a core research in the development of environmental impact assessment based from product design configuration. The Design Information from CAD can provide information in terms of the type of material used, manufacturing process that the product undergoes, and the assembly of its parts. With this information, environmental impact indicators relating to this information which are material recyclability, energy efficiency, process waste, and disassemblability can be assessed respectively. The resulting assessment would be analyzed with other design-decision parameters like cost and other functional requirement (i.e. strength, weight, etc.). Then using an optimization method, the design parameters are improved to achieve the optimum design with the target goals of low environmental impact, low cost and satisfaction of functional requirement. A framework of the over-all research scenario is shown in Figure 3.2. The beauty of this framework is that each focus area of research: Material, Manufacturing and Assembly, can be independent from each other and different methods of analysis and optimization can be explored and developed. Therefore, the focus area of this thesis is in the line of the Manufacturing Process assessment method and design optimization, bounded with a dotted rectangle in Figure 3.2.

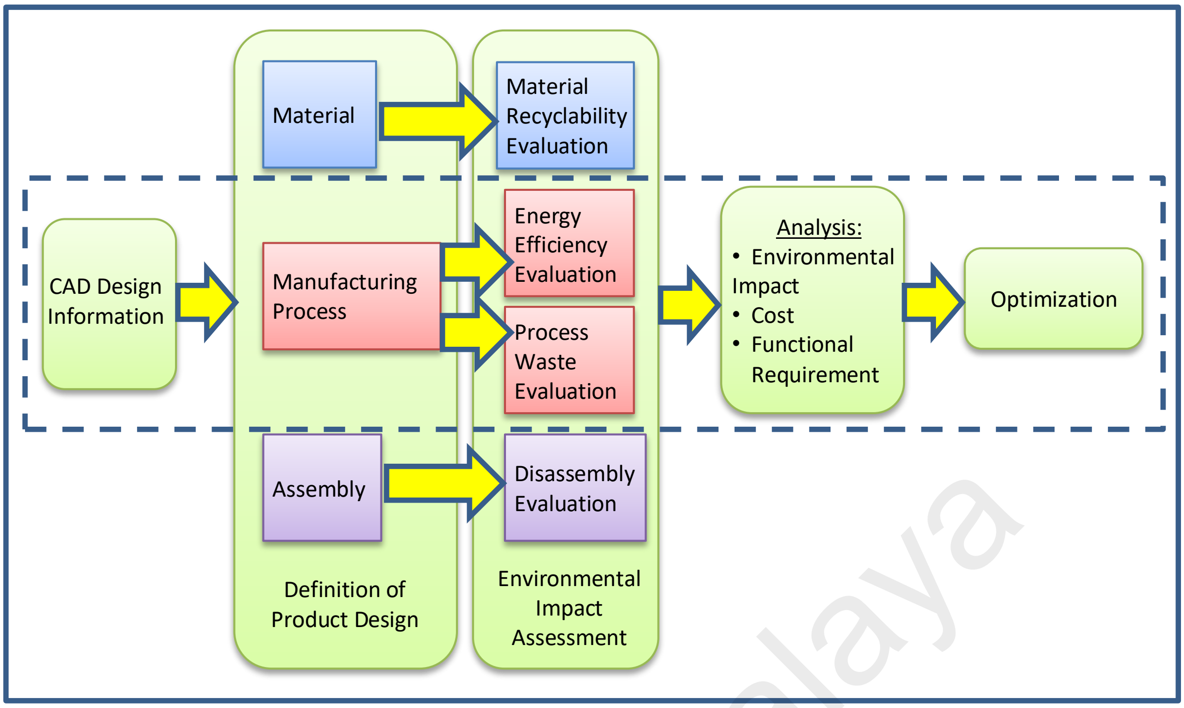


Figure 3.2 Framework of the Sustainable Manufacturing Group Research with the thesis focuses on the Manufacturing Process bounded with a dotted rectangle

Among the different types of manufacturing processes, machining is the most widely used. Due to its sequential nature, this study focuses specifically on the machining process. It can clearly demonstrate the relationship of product design and its potential impact to the manufacturing process because it is possible to assess the machining of each design feature separately.

This section discusses the research methodologies to achieve the objectives stated in Chapter 1.3. It also features the thought process involved in the justification of the usage of some methodologies in this thesis. Below is an overview of how each objective can be achieved and further details are given on each subtopic.

Table 3.1 Overview of Research Methodologies to achieve the research objectives

Objective	**Research Methodology**
To critically review the related literature on current eco-design methods	Literature Review for Framework Development
To develop a method to evaluate the potential environmental impact of a design based on its machining process	Model Development
To demonstrate the methodology through case studies by optimizing the design of a product according to its features with the minimization of potential environmental impact as its target objective	Experimental Validation of Product Cases

3.2.1 Literature Review for Framework Development

The first thing to determine on any research proposal is its viability to be researched. This means that it has to be justified accordingly if it is worth to spend time, money and effort on pursuing the research. For this research, initial studies has been conducted which looks at the general scenario of sustainable manufacturing and eco-design methods. The goals of this methodology are for the researcher to be able to achieve the following:

a) To develop an in-depth understanding of how Eco-design relates to Sustainable Manufacturing (this was discussed in Chapter 2.3 Eco-Design in Product Development). This enables the researcher to understand the mechanics of how design can influences the dynamics of manufacturing, which gives way to the exploration of possible solution approaches which then leads to the development of the framework.

b) To identify the gaps in existing research by reviewing current research trends. This develops the critical thinking of the researcher by pointing out the strengths and weaknesses of the eco-design methods, but at the same time, being able to identify the opportunities for improvement of some methods. It is also practical that the novelty of the research can be drawn out from the solution to the research gaps.

c) To explore possible design optimization methods that could be used based on the limited product information during its Design Embodiment phase. Optimization methods offer design parameter improvement which leads to the eventual reduction of its potential environmental impacts.

3.2.1.1 Survey

Conducting interviews and surveys is not an objective for this research. However, this is a supporting activity in the development of the research framework which is included as research motivations. This led to the evaluation of existing eco-design methods among Malaysian companies. Survey questionnaires were sent to Malaysian manufacturing companies covering the automotive, communication, electronics and furniture sector. The companies that participated in the survey were selected based on the availability of design teams within the company itself. Follow-up interviews were conducted through company visits to better understand the company's eco-design strategies. The questionnaire and interview questions are grouped within the topics listed below:

1. Understanding and awareness about eco design
2. Initial drivers in adopting eco design
3. Responsibility and involvement of stakeholders in eco design
4. Methods/tools/ approaches used

5. Requirements needed for eco design methods/tools. Questions on eco design tools requirements were adopted from (Lindahl, 2006).

The goal of the survey is to acquire the local industrial viewpoint of eco-design which supports the justification of this research. The follow-up interviews also led to the determination of possible threats which could hinder the implementation of eco-design methods. One important possible threat mentioned was the additional work load to a designer's job. Therefore, the development of a model, which will be integrated with CAD, caters to this specific concern of designers.

3.2.2 Model Development

The Research framework from Chapter 2 was developed from merging the findings from the literature review, motivations and the conducted survey. From this framework, a conceptual model of the design-based assessment is developed which focuses on the core of the presented research framework. There are two principal questions that need to be satisfied in the development of the conceptual model. How can the design be evaluated and how can the improvement solution be generated? This section focuses on the concepts and tools used to develop the model.

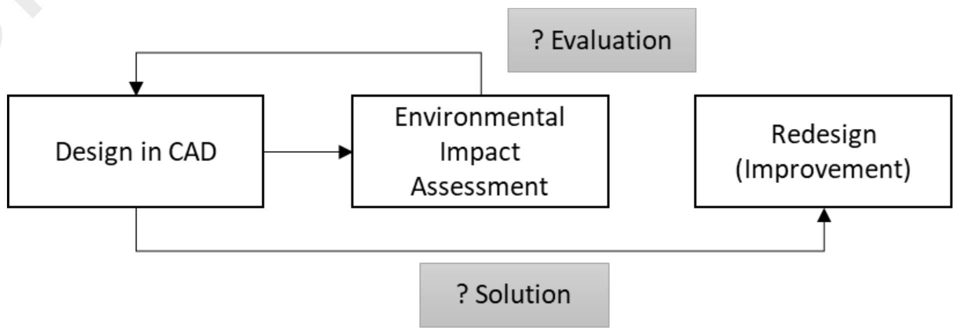


Figure 3.3 Principal questions for the model development

There are 2 problems to take into consideration during the selection of methods for the evaluation:

Problem: The translation of Design into quantifiable information

Proposed Method: Feature-based Design (FBD)

Features are the forms or attributes of a part (of a product) that can be represented as information sets which can be used in reasoning about design, and also the manufacture of the part. Feature-based Design technology is an adequate method to integrate design and its subsequent applications such as engineering analysis, assessment or planning (Salomons et al., 1993).

Problem: Assessment of Design Information

Proposed Method: Life Cycle Inventory (LCI) database from Life Cycle Assessment

A Life Cycle Inventory includes all information on environmental-related inputs (i.e. material and energy consumption) and outputs (i.e. emissions and wastes) associated with a product or service. However, there is no established LCI database that is accepted in a global scope. The current LCI analysis methods are criticized for data quality, technological scope and geographical variations. According to Deloitte LLC (LLC, 2009), the LCA methodology has a false sense of objectivity. Different products using different LCA methodologies and LCI analyses may not be comparable unless they are verified by the same third party certification agency, otherwise, it will be meaningless to compare impacts across competitors. However, in this study, it is valid to use LCA as an assessment method because it is only used to compare the design's potential impacts, which would be used as basis for the design optimization. In this research, several LCI databases were reviewed and tested only for the familiarization of its usage and analysis, though the review of the LCI databases is not a scope of this research.

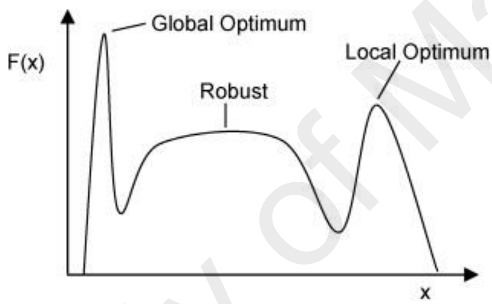
The other principal question in method development is the generation of improved design solutions. There were two possible research approaches that were thought through; first is a decision-making method approach which, from a given set of design solutions, an improved design version is selected based on the assessment of each presented design; second a design optimization approach where the design parameters are modified using different combinations that will generate the best assessment results. Most design optimization methods are automated, which eliminates time as a limiting factor in finding the best solution. The problem with the decision-making approach is that there is a possibility that the representative set of design solutions does not contain the best or optimum solution. Another problem is that it is information intensive which requires several design sets that needs to be generated (mechanical drawings), and eventually each of it assessed and analyzed. The amount of time required for the decision pre-work is dependent on the number of designs to be reviewed. The number of designs to be reviewed is critical because it is a factor in the probability of generating favorable results. A high number of designs to be reviewed will have a high chance of obtaining an optimum design, but this leads to a large amount of work for design generation, assessment and analysis. An optimization method can be suggested as a secondary step to the decision-making approach, but then why bother making a two-step approach, when it can be achieved in a single step (Occam’s Razor).

Problem: Selecting the Optimization method

Determining which optimization method would best suit the proposed model is greatly dependent on the approach to the problem. Since, the focus of the optimization is on the design parameters, it is best to select a method that supports both multi-objective optimization (so that the model will be robust), and constrained optimization (to support other "constraints" to be satisfied).

Chapter 4 provides the detailed discussion of the Design Methodology development. It talks about the technicalities of the design assessment and optimization. It also focuses on the use of Genetic Algorithm as the design optimization method used in this research. Several methods were examined in the Literature Review, but the final selection was between Genetic Algorithm (GA) and Goal Programming (GP). A simple case of Gear box design optimization following the example from Huang (Huang et al., 2006) is applied to both methods. Interestingly, the search methods and the generated results are different. Table 3.2 presents a summary of the observation in results and usage of the methods:

Table 3.2 Observation differences between GP and GA

<table>
<tr><th></th><th>Goal Programming (GP)</th><th>Genetic Algorithm (GA)</th></tr>
<tr><td>Computing time</td><td>Quick and straightforward, results after the click of a button.</td><td>A higher population would require a longer computing time.</td></tr>
<tr><td>Search starting point</td><td>Starting points influence the solution generated as search is limited to its nearby areas.</td><td>Starting point influences from which generation to start the calculation.</td></tr>
<tr><td>Result (Precision)</td><td>The results generated from 10 runs are inconsistent ranging from no solution found to local optimal.


Source: (Rajkumar Roy, et al., 2008)</td><td>The results generated from 10 runs found convergence, and the global optimal.</td></tr>
</table>

Based on the results, GA was opted for the model development due to the following reasons:

a) GA can solve multi-objective and constrained problems, which are needed for the model.

b) Many combinatorial optimization problems from product design and manufacturing are too complex to be solved using conventional optimization techniques (Chu, et al., 2009).

c) The result from GA maintains a pool of solutions, called the Pareto optimal set, rather than just ONE optimal solution. With a given selection of Pareto optimal solutions, it is possible for the designer (or for the user of the proposed method) to make design trade-offs within the set, rather than considering the full range of all the design parameters.

d) Software availability. An existing software GaNetXL was used, which is a Microsoft Excel add-on allowing developers to create their own Genetic Algorithm within Excel.

3.2.3 Case Study and Validation

Since the proposed model is intended for the use of designers, it was considered useful to use a product case study to demonstrate its integration in the design process. With the help of the product case study, the proposed model can also be validated. The aim of the validation is to find out how the proposed model compares with the following:

a) Experimental results – the proposed method is validated by comparing actual machining of each design case and compares the predicted results to the actual measurement of the machine's energy consumption and machining time during the machining process.

   The experiment uses Makino KE55 Milling machine and its machine and electrical specifications are available at the Appendix of this report.

   The actual energy consumption data is collected using a PROVA 6830 Power & Harmonics Analyzer, which measures power usage of the spindle motor, which rotates the tool and the feed motor which moves the table.

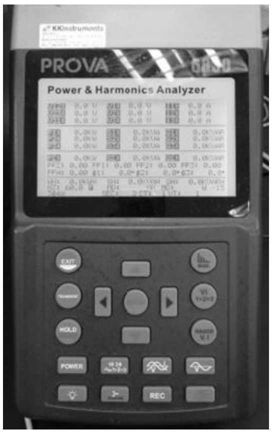


Figure 3.4 PROVA 6830 Power & Harmonics Analyzer

Figure 3.5 Makino KE55 Milling machine with the power analyzer set-up

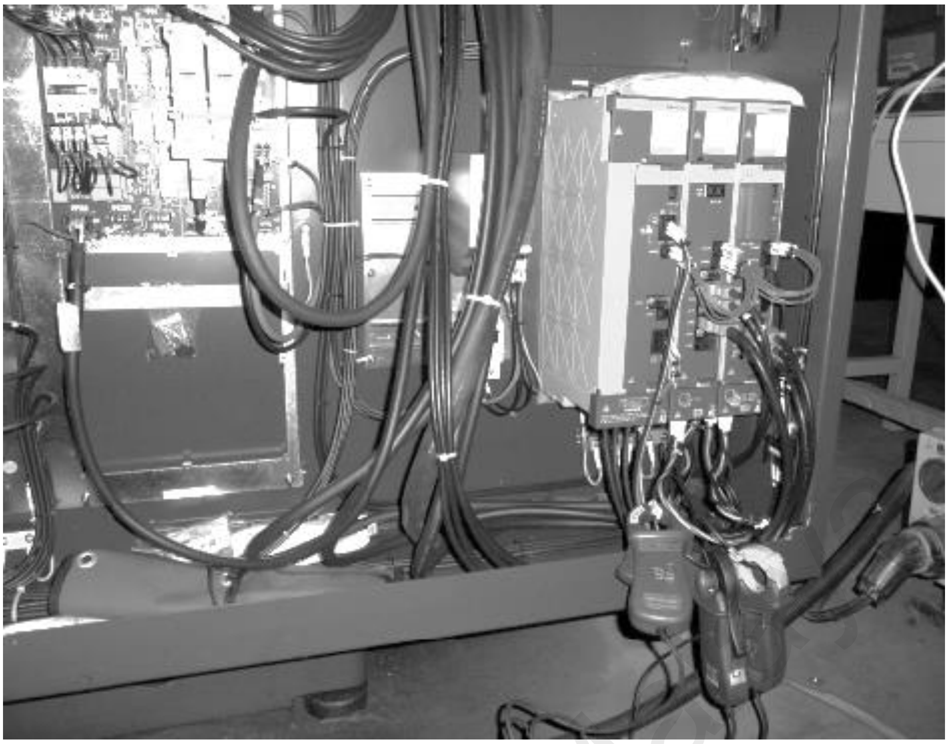


Figure 3.6 Power measurement set-up for the Makino KE55 machine

The actual machining time is collected using a stop watch, using methods similar to time studies. The results of the collected data are compared with the forecasted power consumption and machining time used in the proposed method.

b) Optimization methods – According to a survey about Engineering design optimization in practice (Rajkumar Roy, et al., 2008), the process of design optimization uses mostly expert-based, or design of experiments based optimization approach. Algorithm based optimization, such as GA, are only known to designers as a "potential" technique. The author aims to apply Taguchi method, which is a Design of Experiments (DOE) based optimization, to the product case study and compare to the proposed model the ability to deliver an optimum solution. A detailed method of the Taguchi method can be read in (Ranjit Roy, 2010)

c) Existing Integrated CAD Environmental Assessment tools - Sustainability Xpress for Solidworks, which is a commercially available product design software developed by Dassault Systems is used on the same product case study to have a comparison in an industrial point of view.

Sustainability Xpress for Solidworks provides a quick LCA comparison for different product part designs, which aids in the understanding of environmental impact of design decisions. Using this tool begins with the input of product design parameters namely Material, Manufacturing Process, and the location of the product during its Use phase. These are the parameters for computing the environmental key indicators: Carbon Footprint (kg-CO_{2equiv}), Energy Consumption (MJ), Air Acidification (kg-SO_{2equiv}), and Water Eutrophication (kg-PO_{4equiv}). Greener designs are developed by searching alternate materials that match mechanical and environmental criteria. An option to generate reports to communicate the designs with their environmental key indicators is available.

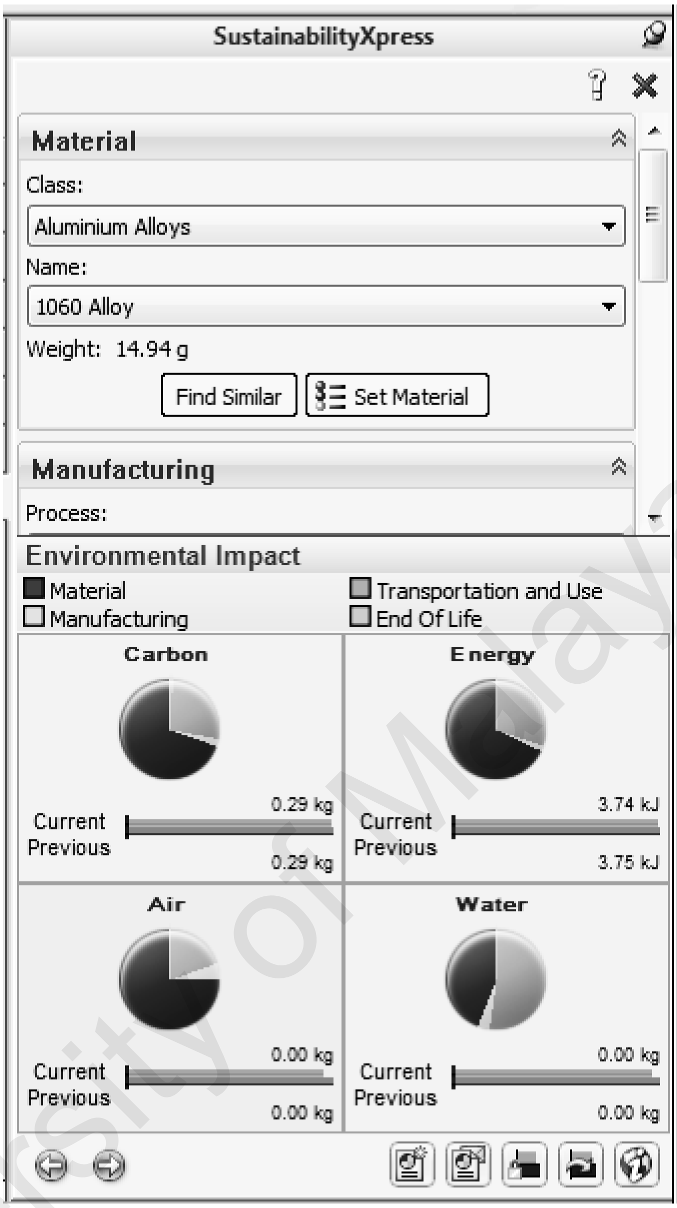


Figure 3.7 Screenshot of the Sustainability Xpress Panel in Solidworks

3.3 Chapter Summary

This chapter discussed the structure of the thesis and its relationship to other on-going research. The thought process involved in the selection of the specific methods to develop the model is presented. An in-depth detail of the technical aspects of the model will be discussed in the next chapter.

CHAPTER 4

DEVELOPMENT OF THE DESIGN METHODOLOGY

4.1 Introduction

After learning the research methods used from the previous chapter, this chapter delves deeper into the development of the proposed design methodology. The reader will further understand the detailed mechanics of how the design method works, which are best explained using figures and formula. The aim of this chapter is to present the detail of the proposed design methodology and the explanation of concepts used behind focusing on the environmental impact assessment and the genetic algorithm principles.

4.2 Integrated Design Solution Framework

The goal of the entire system is to assess the potential environmental impact of the machining process based on the limited design information and generate an optimized design solution to reduce the potential impact of a specific product design. The proposed design framework is composed of two modules as shown in Figure 4.1. The first module is the design evaluation module for the assessment of the product's potential environmental impact using the combination of Feature based-design (FBD) and Life Cycle Assessment (LCA). The second module is for the optimization of the product design according to the least environmental impact and other requirements using the Genetic Algorithm (GA) method. The integrated design solution framework is one of the main novelties of this research work.

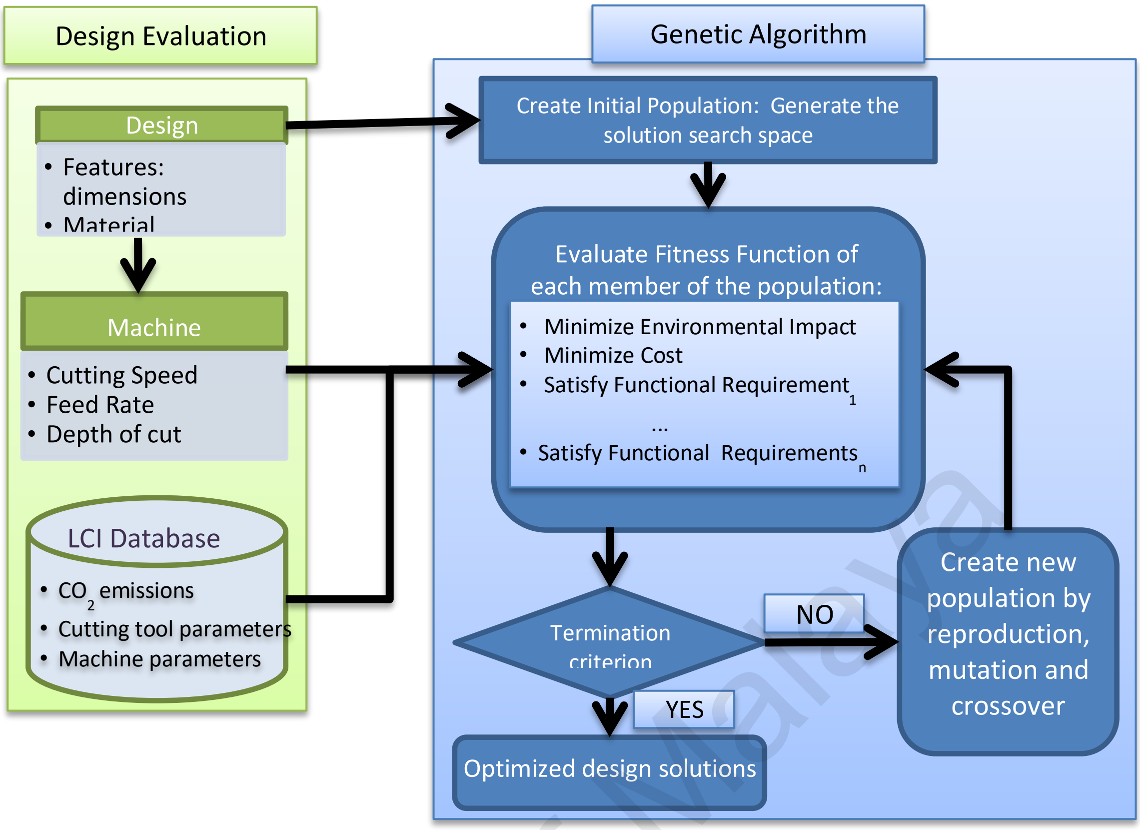


Figure 4.1 Proposed Integrated Design Method Framework

4.2.1 Design Evaluation

As mentioned in the previous chapter, the study focuses on the machining process because of its sequential nature and its ability to manufacture one feature at a time. To evaluate the trade-offs in product design with respect to its potential environmental impact, quantifiable dimensions of machining should be analyzed such as the amount of resources consumed, waste generated and the material removal mechanics. These dimensions can be represented graphically as an Input-Process-Output (IPO) diagram where the definition of input and output of material and resources are as follows (Choi et al., 1997):

INPUT – all resources provided for operation of the process including raw materials, chemicals and power.

OUTPUT – all the products, by-products, waste (solid, liquid, gas), emissions that are generated during processing.

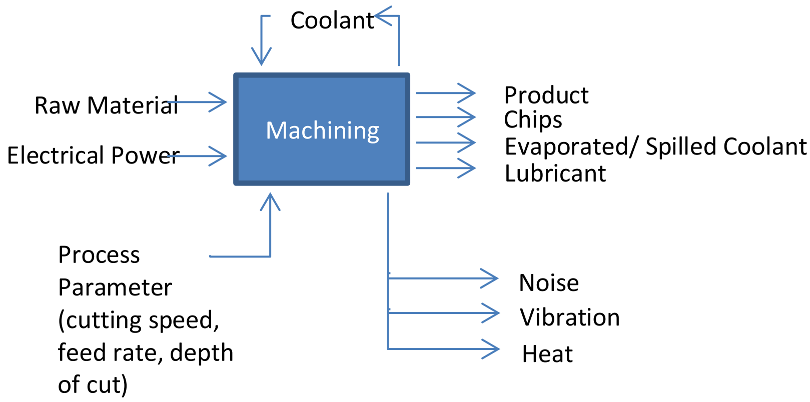


Figure 4.2 Input-Process-Output (IPO) diagram of the machining process based on the study conducted by Choi, et.al. (1997)

All components on the left side of the diagram are the input to the machining process, while on the right side are their outputs. Intangible input by the machinist, the machining parameters: cutting speed, feed rate and depth of cut are also needed to proceed with the machining. Intangible by-products such as noise, vibration, and heat, which also have impact to the health of the workers and to the environment, are also generated. Coolant is also utilized by this process but is not entirely consumed during machining and can be reused again during the subsequent process. Therefore, it is represented as a cyclic process in the IPO diagram.

The goal of the design evaluation module of this study is to assess the product design according to its design requirements with a special focus on minimum environmental impact. This can be achieved by establishing the relationship of the design features to its potential impact by understanding the material removal mechanics. Figure 4.3 presents an overview of how design and manufacture parameters influence the resources utilized and waste generated in the machining process.

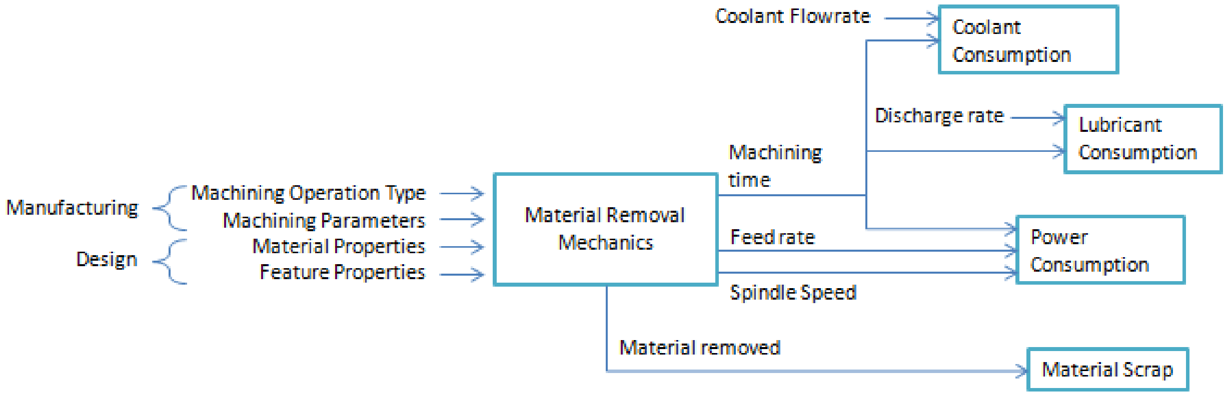


Figure 4.3 Overview of the influence of design and manufacture in the environmental impacts of machining {Adopted from (Munoz & Sheng)}

4.2.1.1 Feature Based Design and Material Removal Mechanics

In design, features contain information of engineering attributes and product definition entities which are the key to its analyses. Moreover in manufacturing, the information that can be extracted from these product features facilitates the planning of the manufacturing processes specifically the machining process type and the machining parameters.

Linking features to the process models leads to the manufacturing knowledge repository as shown in Figure 4.4 (Mäntylä et al., 1996). By identifying the feature, it associates itself to specific types of manufacturing operations possible, which lead to the identification of resource requirements. For example, a given design has a hole feature, which can be further classified as a blind hole, through hole or stepped hole according to its feature taxonomy. Given the selected feature with its classification, the manufacturing specialist/designer can decide on which manufacturing process it is suited for. Looking at its process taxonomy, a hole can be created by milling, drilling or turning depending on the type of resource to be utilized and their availability (tool and machine).

The machining parameters, primarily the feed rate and spindle speed, are dependent on the material to be cut and the tooling to be used, and in some cases the dimension of the tool. Consulting the Machinery's handbook (Oberg et al., 2004) offers the recommended spindle speeds and feed rates for various materials and machining operation type. In Computer Aided Machining, the machining parameters are automatically set based on the recommended values.

Given the design and manufacturing information, it is then possible to quantify the impacts which are discussed in the next section.

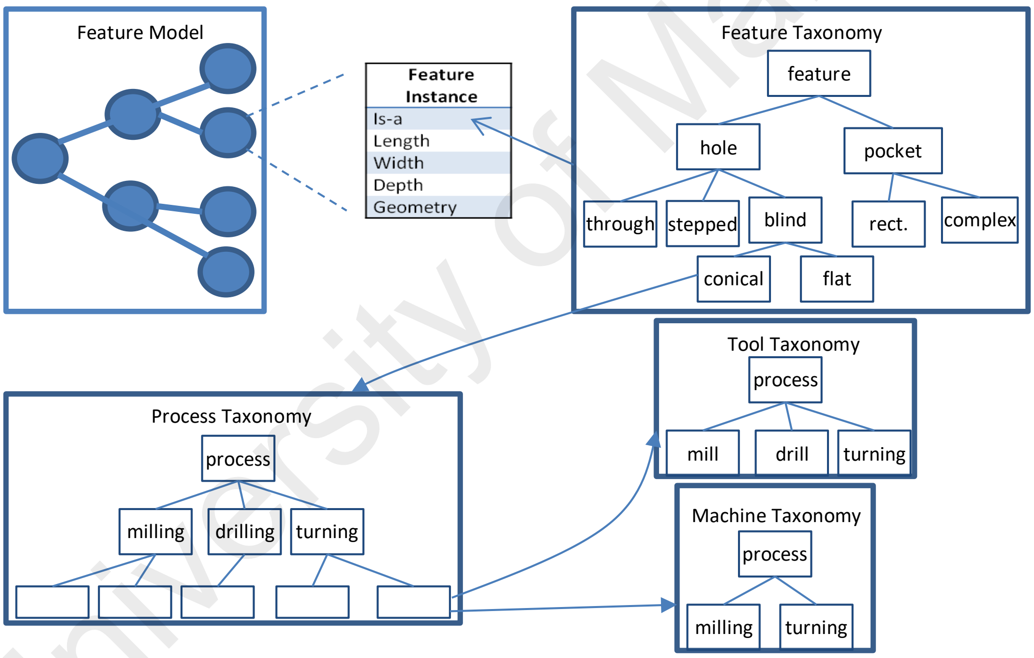


Figure 4.4 Feature-based manufacturing knowledge repository (Mäntylä, et al.)

4.2.1.2 Environmental Impact Assessment

The assessment of impact aims at finding the amount of potential consumption of resources and amount of potential waste to be produced. As discussed in the literature review, these values are best expressed in terms of Carbon dioxide emission equivalent (kg-CO_2). The total equivalent CO_2 emission (potential environmental impact) is calculated from the power consumption of the machine, lubricant oil and coolant consumption, and the amount of chip removed during the machining process by analyzing the machining operations for each feature. Based on the environmental burden analyzer conducted by Narita (2008), the general equation to compute potential environmental impact for each feature developed is shown in Eq. 4.1.

$$Ei = PMi + Ci + Li + Chi \tag{4.1}$$

Where:

Ei : Potential Environmental impact (kg-CO_2)
PMi : Machine power consumption impact
Ci : Coolant consumption impact
Li : Lubricant oil consumption impact
Chi : Chip recycling impact

Machining Time

The most critical factor of the environmental impact (as per Figure 4.3) is the machining time as this is the basis for determining the values of the consumption of the resources. The major factors used in this study to estimate machining time of a feature are: machining parameters, geometry of the feature (dimensions), and the type of machining operation. The required machining time for milling and drilling operations can be estimated using the following formula (Chang et al., 1991):

Milling Operation

$$T = t_m n_p \tag{4.1}$$

$$t_m = \frac{L+\Delta L}{V_f} \qquad n_p = \left|\frac{\Delta h}{a_p}\right| \left|\frac{w}{\propto D}\right|$$

Where:
T : total time of machining operation
t_m : total time for one pass milling
n_p : number of passes
L : length for one pass milling
ΔL : overtravel for one pass milling
V_f : feed rate
Δh : total height of the material to be removed
a_p : depth of cut
w : workpiece width
α : cutting overlap factor = effective cutting width/tool diameter
D : tool diameter

Drilling Operation

$$T = \frac{L + \Delta L}{V_f} \qquad (4.2)$$

Where:
L : depth of the hole
ΔL : clearance height
V_f : feed rate (depending on tool diameter and material)

Machining formulae for other operation types are discussed in the Machinery's Handbook (Oberg, et al., 2004) and Computer-aided manufacturing textbook (Chang, et al., 1991).

Material Removed

The amount of material removed is also a factor to determine the amount of material to be recycled. This can be determined using the Material Removal Rate (MRR) formula:

$$MRR = w \; x \; d \; x \; f \qquad (4.4)$$

Where:
w : width of cut
d : depth of cut
f : feed rate

Power Consumption

To compute the machining power consumption impact PMi as shown in Eq.4.5, the feed rate and spindle speed of the machining operation for each feature is needed in order to determine the feed and spindle motor power respectively. Other peripheral devices such as the NC controller and coolant pump also contribute to power consumption during machining operation. Unlike the feed and spindle motor, whose power consumption is dependent on the varying feed rate and spindle speed, the peripheral devices are dependent on their operational times. Table 4.1 shows the respective feed motor and spindle motor power consumption for varying feed rate and spindle speed taken from published experiments by Arakawa and Aoyama (2007).

$$PMi = LCI(e)\, x\, (PSm + PFm + \sum PP) \tag{4.5}$$

Where:
PMi : Machine power consumption impact (kg-CO_2)
LCI(e) : CO_2 emission intensity of electricity (kg-CO_2/kWh)
PSm : Power consumption of spindle motor (kWh)
PFm : Power consumption of feed motor (kWh)
PP : Power consumption of peripheral devices (KWh)

Table 4.1 Electric Power consumption of components (Arakawa & Aoyama)

Unit Name		Power Consumption (kW)
Spindle Motor	**5000 [rpm]**	**0.25**
	10000 [rpm]	**0.75**
	15000 [rpm]	**1.35**
	20000 [rpm]	**2.15**
	25000 [rpm]	**3.1**
	30000 [rpm]	**4.5**
Feed Drive Motor	**200 [mm/min]**	**0.02**
	1000 [mm/min]	**0.1**
	2000 [mm/min]	**0.2**
	5000 [mm/min]	**0.5**
Cooling System of Spindle		**2.05**
Coolant pump		**0.96**
Lubrication Pump		**0.15**
Chip Conveyor		**0.2**
NC Controller		**0.24**

Coolant Consumption

The coolant is stored in a tank and it uses a pump to supply to the cutting point during machining. It is then flushed back to the storage tank after use and then reused again after being separated from the chips. Some coolant may evaporate due to the heat in the cutting tool, or adhere to the metal chips little by little. Therefore, coolant needs to be replenished, mixed with water to compensate for the loss. Computation of the coolant consumption impact Ci, is shown in Eq.(4.6) below.

$$Ci = \left[\left(LCI(cp) + LCI(cd) \right) x \, Tc + LCI(w) x \, Tw \right] x \, \frac{Mt}{MTTR} \qquad (4.6)$$

Where:

LCI(cp)	: CO_2 emission intensity of coolant production (kg-CO_2/L)
LCI(cd)	: CO_2 emission intensity of coolant disposal (kg-CO_2/L)
Tc	: Total amount of coolant
	: Initial coolant quantity + coolant replenishment quantity (L)
LCI(w)	: CO_2 emission intensity of water distribution (kg-CO_2/L)
Tw	: Total amount of water
	: Initial quantity + replenishment quantity (L)
Mt	: Machining time (s)
MTTR	: Mean time to replenish coolant (s)

Lubricant Consumption

Lubricant oil is used for the slideway, spindle, hydraulic unit, rotary table and double arm changer for the tool magazine. Lubricant application may vary from different kinds of machines, but a general formula to compute the impact would require the running time of the moving parts, the mean interval of lubricant discharges, amount of lubricant discharged and the emission intensity of the lubricant production and disposal, as shown in Eq.(4.7).

$$\mathrm{Li} = \frac{\mathrm{Mt}}{\mathrm{MTTD}} \mathrm{\ x\ Ld\ x\ } \left(\mathrm{LCI(lp)} + \mathrm{LCI(ld)}\right) \qquad (4.7)$$

Where:

Mt	: Running time of moving parts (s)
MMTD	: Mean time to discharge lubricant (s)
Ld	: Amount of lubricant discharged (L)
LCI(lp)	: CO_2 emission intensity of lubricant production (kg-CO_2/L)
LCI(ld)	: CO_2 emission intensity of lubricant disposal (kg-CO_2/L)

Metal Chips Recycling

The last part of the equation deals with the amount of impact by the metal chip removed from the workpiece by machining. Chips are the by-product of the machined final product and the production of its raw material are not considered in this study because it belongs to another phase in the product's life cycle, which is the raw material extraction. On the other hand, these chips are recycled in an electrical heating furnace to be melted and re-sold again in various forms. Recycling these chips causes environmental impact because of the electric consumption on furnace use. Impact values are dependent on the type of metal and its weight (kg-CO_2/kg) so determining the total weight of the chips removed is the key component, as shown in Eq.(4.8).

$$Chi = (WpV - PV)\ x\ d\ x\ LCI(m) \qquad (4.8)$$

Where:
WpV : Workpiece volume (cm^3)
PV : Product volume (cm^3)
d : material density (kg/cm^3)
LCI(m) : CO_2 emission intensity of metal chip recycling (kg-CO_2/kg)

Equivalent CO_2 emissions

Normally, LCA impacts are categorized according to the types of emissions to the environment: from global warming, ozone layer depletion, human toxicity, energy resource depletion, and the like. However, this study focuses on the global warming potential (GWP) as an environmental impact. GWPs allow scientists and policymakers to compare the ability of each greenhouse gas to trap heat in the atmosphere relative to other gases. GWP of a greenhouse gas is the ratio of radiative forcing, from 1kg of greenhouse gas, to 1 kg of CO_2 over a hundred years. CO_2 was chosen as a reference gas to be consistent with the Intergovernmental Panel on Climate Change (IPCC) (Forster & Ramaswamy, 2007). The emission data used in this study were compiled from different LCI database tables and from the Embodiment Energy Emission Inventory Data (3EID) compiled by Narita (2006) summarized at Table 4.2.

Table 4.2 CO_2 equivalent emissions involved in Machining

CO_2 equivalent emissions	
Electricity (kg-CO_2/KWh)	0.381
Coolant production (kg-CO_2/L)	0.9776
Coolant disposal (kg-CO_2/L)	0.0029
Lubricant production (kg-CO_2/L)	0.469
Lubricant disposal (kg-CO_2/L)	0.0029
Aluminum chip recycling (kg-CO_2/kg)	0.0634
Steel chip recycling (kg-CO_2/kg)	0.052
Grey Cast Iron chip recycling (kg-CO_2/kg)	0.055
Water Production (kg-CO2/L)	0.189

4.2.2 Design Optimization using Genetic Algorithm

Genetic algorithm searches for an optimum solution similar to how natural evolution takes place. GA creates a collection of solutions (population of individuals) from where it performs its search. An individual is represented as a chromosome, which is composed of bit information called genes. GA alters the gene information of a chromosome retaining the "good" information which represents the inheritable property of an individual. Similar to the Darwinian Law of natural selection (survival of the fittest), each individual is assessed according to the fitness function used (assessment criteria). The selected fit individuals are kept in the population pool in order to reproduce with other individuals. The unfit individuals are eliminated. A new population is created from the intersection of two individuals (parents) by method of unary and binary operators (mutation and crossover). Therefore, the new generation of population will resemble the chromosomes of the successful parent individual. Whoever is the "fittest" among the generation will survive and carry on the reproduction process. Table 4.3 presents the correspondence of terms between design information and the terminologies used in GA.

Table 4.3 Correspondence of terminologies between design information and GA

GA terminology	Design terminology	Definition
Gene	Feature information (dimensions, form, material)	Part of the chromosome that represents the whole solution
Chromosome	A single design scenario	Representation of the solution
Population	Collection of possible design solutions	All the solutions within the given limits
Individual	Product Design	Solution to a problem
Crossover	Binary search operator	
Mutation	Unary search operator	
Reproduction	Reuse of solutions	
Selection	Retaining fit individuals	
Fitness	Goal, the criteria to be satisfied in the search process	

4.2.2.1 Definition of Design parameters into GA

When designing GA for a given problem, the first step is to represent the problem in terms of GA terminologies. Feature-based design is the methodology incorporated with GA because each design and feature parameter can be easily represented by a gene. Parameters can include its dimensions, material type, form function, etc. as long as it can be represented in strings or data bits. The value in each gene is restricted to the values within the design allowable limits. These limit values are based from the decision of the designer. A single information is allocated per gene, and collectively comprises the whole design scenario, or the chromosome.

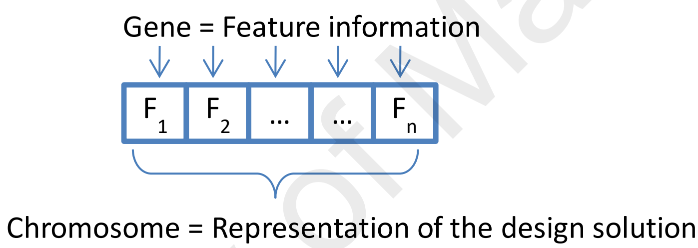


Figure 4.5 Chromosome structure in GA

Numerical values are assigned to each parameter variable and the maximum allowable value for the gene is dependent on the design limits of the product. For example in Table 4.4, there are 3 defined possible material options for this product, therefore, each option corresponds to one gene value. The length of the chromosome is dependent on the number of parameters that are to be optimized. The collection of genes in one chromosome represents one design scenario. Figure 4.6 shows three sample chromosomes and how these chromosomes differ in designs.

Table 4.4 Sample of gene representation for each feature information

Parameter	Gene Representation		
Material	1 = Aluminum	2 = Steel	3 = Gray Cast Iron
Profile cut	1 = Yes	2 = No	
Stock size	1 = Half	2 = Whole	
Offset cut	3 = 3mm	4 = 4mm	5 = 5mm

	Material	Profile cut	Stock size	Offset cut	Screw diameter	No. of screws	No. of pockets (upper half)	No. of pockets (lower half)	Fillet radius	Thickness
Design X	2	2	1	5	4	1	0	0	8	3
Design Y	3	1	1	5	2	5	2	0	8	7
Design Z	1	1	2	4	2	0	2	2	3	5

Design X Design Y Design Z

Figure 4.6 Sample of chromosome representation

There are 10 genes that comprise each chromosome (designs) in Figure 4.6. Design X for instance, has the value of 2 for the first gene, which contains the material information, 2 for the profile cut, 1 for the stock size, etc. This means that it will use Steel (based on Table 4.4) for its raw material, no profile cut, only half of the stock is used, and so on. In some complex cases, the chromosome can also be represented with its length as a variable. These are circumstantial cases which follow an IF-ELSE computing scenario. There is no exact method in choosing the right way of representing problems to GA. Using simple representations might spend too much time searching irrelevant regions of search space. On the contrary, putting too much domain knowledge may result for the offspring to be too far away from the parents without reaching equilibrium (Renner & Ekárt, 2003).

4.2.2.2 Population Generation

GA works by maintaining a population of solutions (chromosomes) from which to select, mutate and crossover. The population size is important as it determines the diversity of the population at the start of the run and also how long it takes to run. The population size is also the resulting number of solutions that will be presented as optimal solutions. As mentioned in chapter 3, this study will be using NSGA II method which means that the results of the search sequence are all optimum solutions based on the Pareto optimal front. An increase in the value of the population size also means a longer time to complete its run. Therefore, choosing the population size is dependent on the number of optimum solutions that the designer would want to select from, and on its computing time.

4.2.2.3 Fitness Functions

The survival of an individual is determined by its fitness. This serves as a filter to separate the less fit and allow the fitter solutions to evolve into better solutions. In order to achieve this, the fitness function should have results that contain evaluative indication of how well the solution fulfills the objectives of the problem.

In this study, the designs are focused on its evaluation in terms of the amount of environmental impact, which can be computed using the formulae mentioned in the previous section. The less impact a design generates, the "fitter" the design solution. Normally in design cases however, designs are optimized not only on a single criteria but depending on the design goals/requirements, it is usually more than one. This is where we can appreciate the beauty of GA because it deals with multi-objective optimization, where it searches for a Pareto optimal solution based on multiple fitness functions. According to the results of the conducted surveys and interview (Sakundarini et al., 2010; Taha, et al., 2010), cost minimization is the number one criteria that the customers prioritize. Also, the product's functional requirements are important criteria that need to be satisfied like its compressive stress, total weight, etc., which can all be evaluated from its design. These multiple criteria can be accommodated by GA.

Sometimes, the evaluation of the fitness functions is performed using a third hand software, which passes the assessment results of each individual to the GA program. This could be time-consuming which may result to the slow response in GA.

4.2.2.4 Genetic Operators

Genetic operators are applied to each generation that passes through the "filter" in order to create a new population. There are three main genetic operators that can be used namely Reproduction, Crossover and Mutation.

Reproduction – It is possible to create a population by directly copying the fit solutions without implementing any changes on its chromosome. This provides a possibility of survival for already optimum solutions.

Crossover – it is a binary operator, which means that it is designed to share information between two individuals to create entirely new individuals which have some of the attributes of their parents. Two offspring are created by crossing over two parents, and they are often better solutions that either of their parents, but also occasionally worse. Crossover occurs by splicing the chromosome at a particular point(s) on each chromosome and then recombining one section of Parent A with the opposite section of Parent B.

The choice of crossover operator can influence the effectiveness of the genetic algorithm:

Simple One Point

A single location in the chromosome is chosen. Child A consists of all the genes located before this crossover point of the parent A, and the genes after this crossover point of parent B. Similarly child B consists of the first portion of parent B and the second portion of parent A.

Simple Multi Point

Multi-point crossover acts in the same way as single-point, but multiple points are selected along the chromosome. This leads to a better distribution of genes across the offspring.

Uniform Random

Uniform crossover is essentially the ultimate case of multi-point crossover in that it selects each gene at random to be part of either child A or child B. This makes the distribution of genetic material independent of the position of the gene in the chromosome.

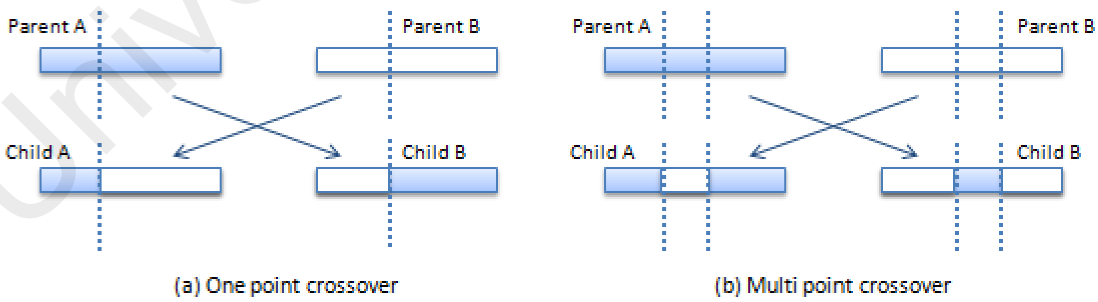


Figure 4.7 Types of crossover

Mutation – It is a unary operator designed to provide new genetic material during optimization. Without the mutation operator, the algorithm could find locally optimal solutions without searching for better globally optimal solutions. The mutation operator works by selecting a gene at random in a chromosome and changing it to a random value (within the bounds of the gene). This is performed within a certain probability, specified by the user.

4.2.2.5 Selector

Only successful individuals are allowed to have offspring. The selection of these individuals is based on their fitness. This study uses the Tournament selection method where two solutions are chosen at random from the population and compared. The solution with better (lower) rank wins. If both solutions have the same rank then the solution with larger crowding distance wins. In case that both solutions have the same rank and also crowding distance then winner is chosen randomly.

4.2.2.6 Constraints

Constraints are used when a certain objective is penalized for going out of the range of allowable values. For example in a multi-objective problem, if one of the objectives is the cost of the solution and the limit is $100, then the solutions outside this value are ignored. The constraints are defined from Excel formulas and linked to the necessary objective to be penalized if the cases are not satisfied.

4.2.2.7 Results

For a multi-objective optimization problem, there is no single solution that exists which is the optimum solution to all the objectives given. In cases of conflicting objectives where trade-offs have to be made, the Pareto optimal solution exists. Pareto optimal solutions are mathematically considered equally good solutions because vectors cannot be ordered. Given this, multi-objective optimization problems would result in different solutions depending on how the problem is perceived, and the goal is to find the solution that would satisfy the human decision maker.

4.2.3 Integration of Design Evaluation and GA

When using GA to solve design problems, the first step is to define how the design scenario could fit in GA (Section 4.2.2.1). The problem to be solved particularly in this study is, "How can design influence and reduce the potential environmental impact of the machining process?" Given this statement, GA searches for the best solution according to the fitness functions defined (Section 4.2.1.2). Returning to the proposed integrated design solution framework (Figure 4.1) presented at the start of this chapter, this study developed a semi-automated methodology divided into two parts:

Design Evaluation

After design conception, the designer uses different methods to embody a design. Modeling techniques like the use of CAD software can predict the product's performance under certain conditions. In this research, the use of CAD software, Solidworks, is used to visually represent the product and is also the source of the design feature information. On the other hand, the assessment of designs is implemented using Excel, where all the formula related to the environmental impact is developed. It also includes the database of machining information for different material types and manufacturing operation and the LCI database of the environmental impact emissions of the processes involved in the machining operation.

The integration of Solidworks and Excel is possible through the use of Design Tables. This is a feature where designers can try out different design scenarios which are useful for product evaluation. This manual-based method works accordingly:

a) The designer identifies which design parameters are to be optimized.

b) These parameters are added to the design table (in Excel), in which any changes in the value of the parameters will immediately reflect the CAD model. This is also an important step to evaluate the design based on its limitations because values that would not present a feasible solution for the design can be determined by flashing a warning message. More information about design tables provided using the Solidworks help guide (Systems).

c) The parameters in excel format serve as the basic representation of the design, which is to be evaluated in the same Excel sheet with all the fitness functions required.

d) Linking the correct design parameter to the fitness function formula is possible using basic excel functions. The resulting values based on the evaluation of the manufacturing processes and environmental impact are automatically displayed.

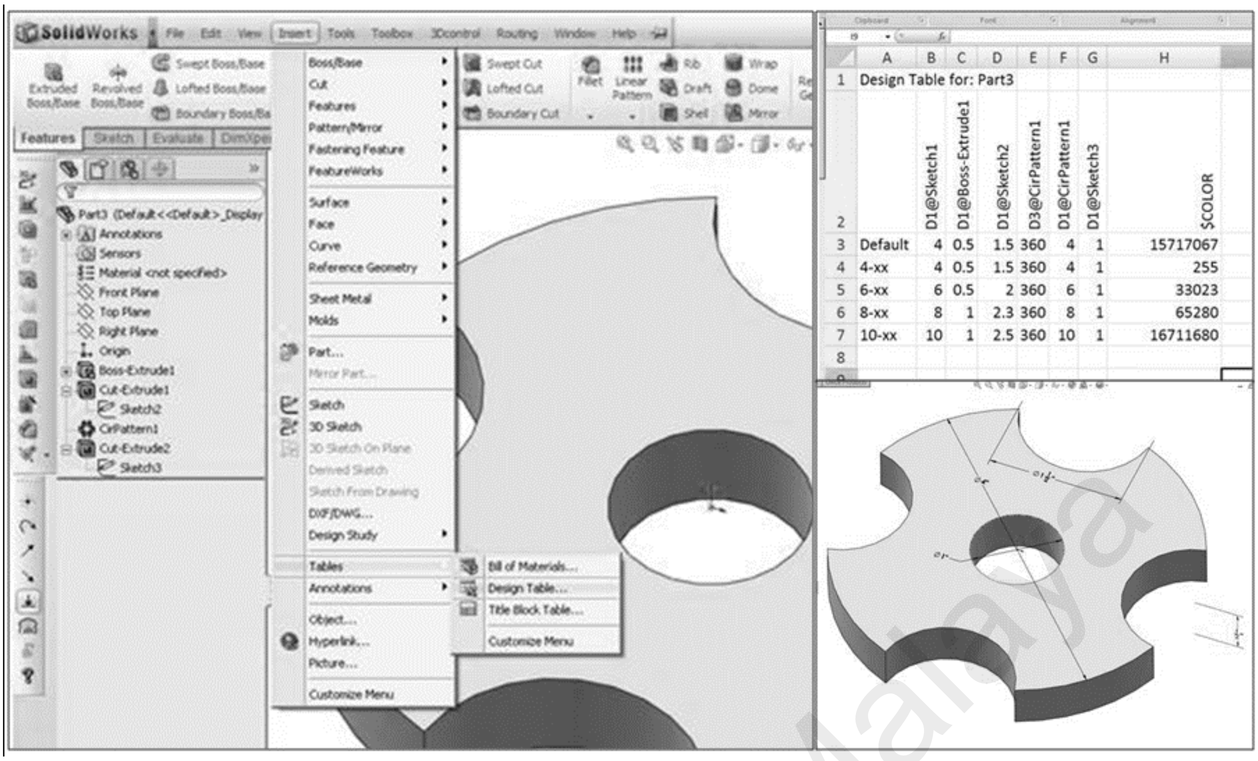


Figure 4.8 Design Table in Solidworks (Smith)

Genetic Algorithm

The parameters that need to be optimized (chromosome) are represented in Excel format and the success of the search is dependent on its successful evaluation of fit individuals. This would require the automation of its assessment because GA will have to evaluate an exponential number of individuals for every new generation. The chromosomes are an input in cells (in Excel) that are next to one another, which is called the “base chromosome”. The formulae of the fitness functions are linked to the cells containing the genes of the base chromosome. Therefore, a change in value of the genes would lead to an automatic change of value in the results of the fitness functions. To accommodate the integration of the GA and the Excel worksheet, this study uses a rapid optimization tool for Spreadsheet-based models based on the study by Bicik, et.al.(2008) called GanetXL, as an Excel add-in program, which automates the iterative processes of Genetic Algorithm as follows:

a) GanetXL randomly generates an initial population within the limits of the possible design solution given.

b) Each of the chromosome members from the generated population is passed to the assessment formulas in Excel to evaluate how it satisfies the fitness functions.

c) The termination criterion is a predefined number of iterations based on the number of generations to be repopulated.

d) A new generation of the population is created based on the selected chromosomes that satisfied the fitness function. The selected chromosomes apply genetic operators and they reproduce, crossover, and mutate with each other resulting to their next generation offspring.

e) The new generation of population is once again evaluated as in the second step until the termination criterion is satisfied.

f) Once the termination criterion is satisfied a set/s of design solution are presented and the designer can choose appropriate design solutions suited based on other design requirements.

GanetXL can access the base chromosome by setting its location in the Excel sheet manually to its user interface and by indicating the upper and lower limit values of each gene. The objectives of the optimization also need to be defined manually and to set the location cells of the results of the fitness function (i.e. in Figure 4.9, Environmental Impact, cost and Weight) and the objective whether to minimize or to maximize them. Genetic Algorithm operators can also be selected from the user interface as well as defining the population size and the number of iterations that the GA would run, which determines its termination criterion.

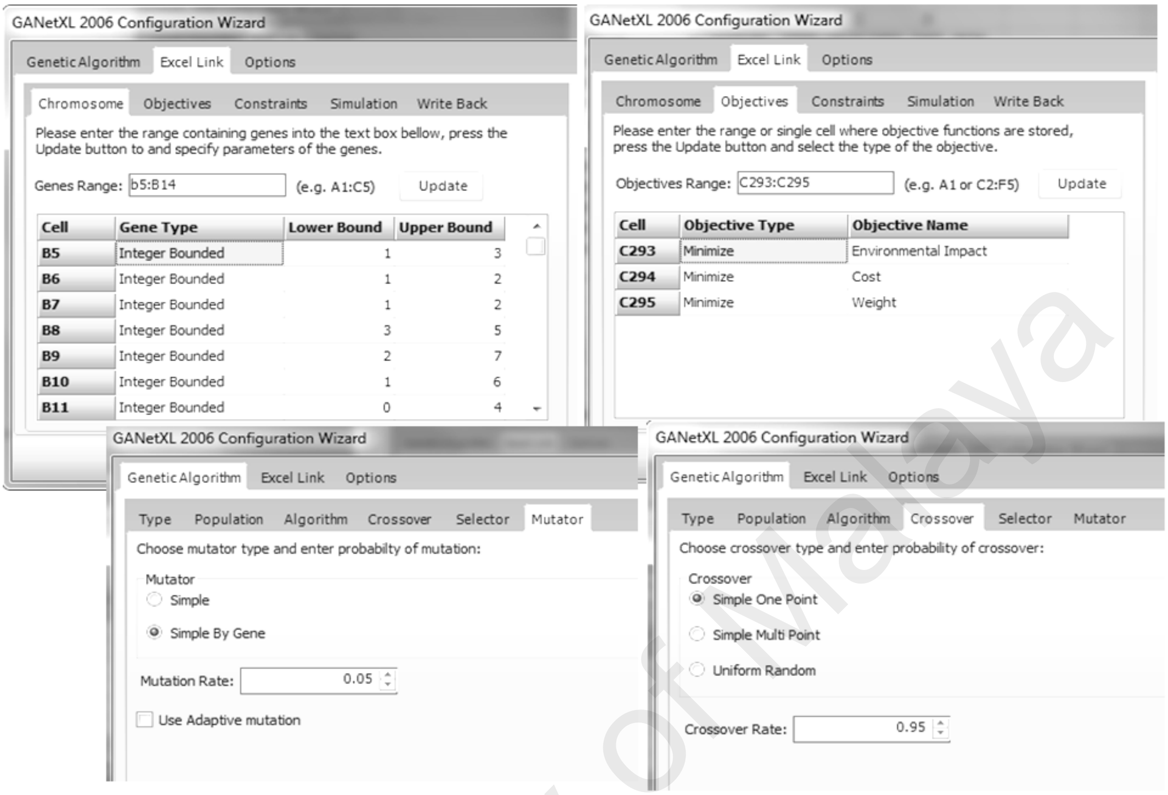


Figure 4.9 Snapshots of GanetXL

4.2.4 Selection of Solutions

The result from GanetXL is a pool of individuals, which are the final set of individuals which have been selected as the fittest individuals according to the fitness functions. The result is projected to a new Excel sheet (Figure 4.10) listing each gene value in each column with the corresponding results of from the evaluation of the fitness functions for each specific objective (i.e. Environmental Impact, Cost and Weight).

ID	G0	G1	G2	G3	G4	G5	G6	G7	G8	G9	Environmental Impact	Cost	Weight
62468	1	1	2	3	6	4	4	4	4	3	0.322966086	3187.325	0.078608
156485	1	1	1	3	7	5	4	1	15	3	0.180605292	2807.52	0.084467
64361	1	1	1	3	7	2	4	0	15	3	0.178879832	2802.568	0.084983
62672	1	1	1	3	7	6	4	2	4	3	0.17498371	2781.333	0.08577
156378	1	2	2	4	3	1	0	0	3	3	0.07088817	1916.726	0.109419

Figure 4.10 Screenshot of the results generated by GanetXL

Using NSGAII The number of resulting chromosomes is equal to the population size initially defined. From this pool of results, the designer will still have the additional task of choosing the ideal design. It is possible to have a population size of 1 (and avoid the additional task of design selection), and accept the resulting single solution as the final choice. However, according to Koljonen, et.al (2006), optimization reliability increases with population size. It is advisable to maintain a population size more than one to improve the reliability of GA and therefore a method of solution selection is suggested depending on the problem's objectives.

Ranking method – for single objective optimization, a straightforward method of selecting the best solution among the pool of individuals is by simply sorting the chromosomes according to its satisfaction of the objective. The one which satisfies the objective the most is of course the best solution.

Weighted Average method – for multi-objective optimization, each objective would be given a certain priority over others and weights are established to define those priorities. This means that the problem is more complex and a straightforward ranking method is not enough. The weighted average method can be established in two steps:

a) Normalization – normalizing the results of the fitness functions into a single scale measure. This requires knowing lowest and highest values in order to define the range of the scale.

b) Weighting the criteria – the summation of the product of the weight of each objective and the normalized values of the results. In cases of equal priorities, weights are equally distributed among the objectives.

4.3 Chapter Summary

A semi-automated methodology of two parts is presented in this chapter. It consists of the Design Evaluation, which deals with the representation of the design in terms of Genetic Algorithm terms and the design assessment using the combination of machining information taken from the machining standards, and the life cycle inventory database. The methodology employs the use of a CAD software (i.e. Solidworks) to translate the product design parameters into a recognizable format in Excel for the product assessment. This is successfully done using Design Tables. The second half of the methodology is the automated Genetic Algorithm method which employs the use of an add-in to Excel called GanetXL. This deals with the automation of population and the comparison of each of the assessment results among the individuals. The result of GanetXL is a pool of individuals, which represents the Pareto optimal solutions. From these individuals, the designer can choose the best solution depending on their priority by ranking method or weighted average. An in-depth understanding of this proposed methodology can be achieved by applying it in a case study, which will be discussed in the next chapter.

CHAPTER 5

CASE STUDY: DESIGN OF A CAM PLATE

5.1 Overview of the case study

To illustrate the application of the proposed system, a case study is conducted on a product that undergoes CNC machining as its primary manufacturing process. The product to be investigated is a cam plate that would assist the movement of a cam follower in a specific curve design. The goal of the case study is to validate the methodology proposed by finding the optimum design of the cam plate based on the least environmental impact, least cost and lightest assembled weight. This study limits the analysis of costs and impact within the bounds of the manufacturing stage of the product and that the three criteria are of equal priorities to be satisfied.

5.1.1 Product Definition

The product is a cam plate to assist the movement of a cam follower in a specific curve design. The assembly is composed of a camshaft, which rotates providing the movement for the entire system, and the cam plate. On certain design scenarios, the system may require screws to attach the cam plate on a back plate, which keeps the cam plate in place.

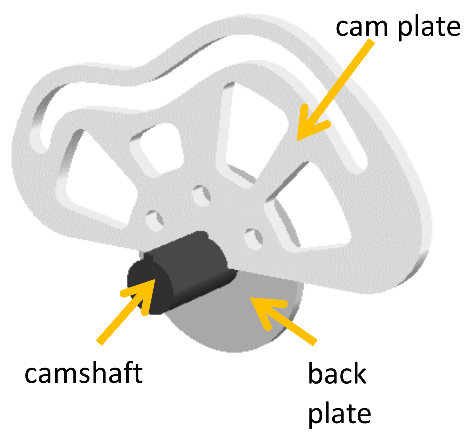


Figure 5.1 Cam plate assembly

The product design must satisfy the following requirements:

a) Priority: Aid the movement of the cam follower in a given curve

b) Machining with minimum environmental impact

c) Minimum manufacturing cost

d) Minimum Assembly weight

e) Safe design, no sharp edges

The cam plate consists of several features that are important to the function and form of the product. There are three primary features in the product which are crucial to its main function of cam movement:

a) The curve profile where the cam follower will traverse - this is a defined curve, which facilitates the designated movement of the cam follower

b) Hole – designed for the camshaft

c) Keyway – designed for the key in the shaft

These primary features have fixed dimensions and form, therefore, when it comes to optimizing its design, they retain their form and dimensions. The other features of the product are for the improvement of the design towards its satisfaction of the requirements. They have a wider range of allowable values, which can be optimized to find the best design solution:

a) Stock size – The important part of the cam plate is the upper part where the curve profile is located. Therefore, it is an option to just use half of a disk stock for the cam plate, which is similar to the one shown in figure 5.1. This means that two cam plates can be made from a single disk stock, which could lead to cheaper production. However, the trade off would be the additional work of cutting the stock into half, which leads to additional stock cutting cost. Another trade off is that since a half stock could not attach itself on its own to the cam shaft, a back plate is required to be screwed to the cam plate, which may add to the weight of the assembly. Using a whole disk stock for the cam plate, on the other hand, may also be heavy for the whole assembly, but this does not require additional screws and back plate because it can attach itself to the cam shaft.

b) Material – the type of material determines the machining parameters to be used. It also affects the impact of the recycling of chips and the total mass of the assembly.

c) Profile cut – Reducing the amount of material in the final product may improve the product's material efficiency and of course its weight, but this also means additional use of power to machine it and waste generated. This is complemented with the value of the offset cut, which is the distance from the curve where the removal of material will commence.

d) Pockets – Similarly with the profile cut, its purpose is to reduce the amount of material in the final product.

e) Screws – In design scenarios where half of the stock is used, screw holes and screws are required to fasten the cam plate with the back plate.

f) Fillet – This feature is to reduce the sharp corners of the product in cases when half tock is used.

g) Thickness of the cam plate

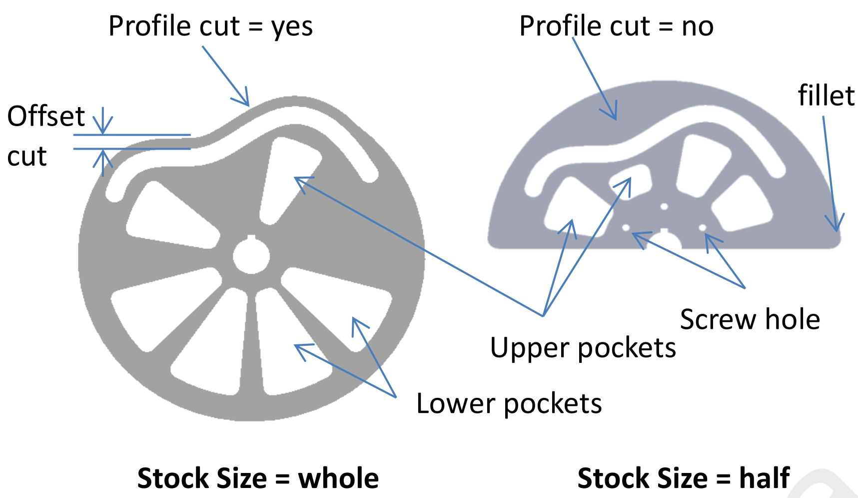


Figure 5.2 Features of the cam plate

To find the optimum design to satisfy the given requirements, the parameters shown in Table 5.1 are investigated using the different design parameter alternatives given. These design parameter alternatives serve as the limiting boundaries of the design and this defines the area of the search space in GA.

Table 5.1 Design parameter boundaries for optimization

Parameter	Design Parameter Alternatives
Material	Aluminum/ Steel/ Gray Cast Iron
Profile cut	Yes / No
Stock size	Half / Whole
Offset cut	3-5 mm from the curve. If profile cut = NO, offset cut = 0
Screw diameter	2-7mm screw holes. If stock size = whole, screw diameter = 0
No. of screws	1-6 screws. If stock size = whole, no. of screws = 0
No. of pockets (upper half)	0-4 pockets
No. of pockets (lower half)	0-4 pockets. If stock size = half, no. of pockets = 0
Fillet radius	3-15mm. If stock size = whole, fillet radius = 0
Thickness	3-7mm

5.1.2 Chromosome Representation

The parameters are translated into gene by representing each into numerical values. For the cases of the Material, Profile cut and Stock Size parameters which are non-numerical in nature, these have to be represented by assigning numerical values for each. For the remaining parameters, their own numerical values serve as its gene values. The gene values are not only limited to integers, but also to real numbers. A summary of the parameters represented in gene values is shown in Table 5.2.

Table 5.2 Gene representation of the design parameters to be optimized

Parameter	Gene Representation					
Material	1 = Aluminum		2 = Steel		3 = Gray Cast Iron	
Profile cut	1 = Yes		2 = No			
Stock size	1 = Half		2 = Whole			
Offset cut	3 = 3mm		4 = 4mm		5 = 5mm	
Screw diameter	2=2mm	3=3mm	4=4mm	5=5mm	6=6mm	7=7mm
No. of screws	1 – 6					
No. of pockets (upper half)	0 – 4		Represented by their numerical values			
No. of pockets (lower half)	0 – 4					
Fillet radius	3 – 15 mm					
Thickness	3 – 7 mm					

5.2 Design Evaluation

5.2.1 Definition of Fitness Functions

The fitness functions are based on the main objectives of to be satisfied namely: minimum environmental impact, minimum cost and lightweight product assembly. For the computation of each function, there are several assumptions considered:

Machining Assumptions:

a) Machine considered for the machining of the product is a CNC High Speed Milling machine with max RPM of 5200.

b) The initial stock material is a Solid Cylinder

c) The machining parameters (i.e. Spindle Speed and Feed rate) are dependent on the type of material to be machined, the machining operation and the tooling to be used.

d) Carbide tool is used for the facing operations, while High Speed Steel (HSS) is used for general machining operations

e) The machining time for each operation is based on the basic machining formulas as discussed in Chapter 4

f) The amount of material removed is based on the Material Removal Rate

g) The machining process for each feature is as follows:

Feature	Process
Thickness	Facing
Hole	Drilling
Screw Hole	Drilling
Pocket	End Milling - Rough & Finish
Profile	End Milling - Rough & Finish
Fillet	End Milling - Finish

Cost Assumptions:

a) Stock cutting is included in the material cost computation

b) 100% of the material removed (chips) are to be recycled

5.2.2 Environmental Impact Assessment

The formula for computing the environmental impact was discussed in chapter 4, and this is demonstrated using a sample design scenario from the case study.

Sample Chromosome for Assessment:

	Material	Profile cut	Stock size	Offset cut	Screw diameter	No. of screws	No. of pockets (upper half)	No. of pockets (lower half)	Fillet radius	Thickness
Design Z	1	1	2	4	2	0	2	2	3	5

Design Z

Table 5.3 Machining time (secs) for each machining operation:

Design Z
Material Aluminum

Machining Operations	**Machining Time (s)**
Facing	11.54
Hole Drill	5.78
Slot Rough	42.39
Slot Finish	45.66
Pocket whole rough	39.71
Pocket whole finish	89.93
Lower pocket rough	45.06
Lower pocket finish	95.55
Profile Rough	21.35
Profile finish	60.05
Total Machining Time	457.02

Computation for Energy consumption impact (PMi):

The following assumptions are considered for the Facing Operation:

Tool = Carbide
Spindle Speed = 5200 RPM
Feed rate = 1872 mmpm
Machining time = 11.54 secs

Interpolating the values from the electric power consumption of components from Chapter 4 Table 4.1 using the given feed rate and spindle speed would result in the following:

POWER RATING OF COMPONENTS (KW)	
FEED DRIVE MOTOR	0.18
SPINDLE MOTOR	0.25
PERIPHERAL DEVICES	
NC CONTROLLER	0.24
COOLING SYSTEM OF SPINDLE	2.05
COMPRESSOR	1
COOLANT PUMP	0.25
LIFT UP CHIP CONVEYOR	0.1
CHIP CONVEYOR IN MACHINE TOOL	0.6
TOTAL	**4.67**

Using equation 4.5 to compute the Machine power consumption impact (PMi), the summation of the power consumption of components have to be translated in terms of KWh, which means that the total power rating has to be multiplied to the machining time to determine the amount of power that a particular operation is to be used (KWh). From equation 4.5 and the CO_2 equivalent emissions Table 4.2 (Electric consumption = 0.381 kg-CO_2/KWh), we get:

$$PMi = LCI(e)x\ (PSm + PFm + \sum PP)$$

$$PMi = 0.381\ kg - \frac{CO_2}{KWh} x\ (4.67\ KW\ x\ 0.0032\ h)$$

$$PMi = 0.0153\ kg - CO_2$$

The total PMi for the Facing Operation alone is 0.0153kg- $CO_{2.}$ The power rating for the feed drive motor and spindle motor varies depending on the type of machining operation and the recommended spindle speed, that is why it is not a straight forward computation and could not directly multiply the total machining time with the total power rating of all components. However, for peripheral devices are independent from these parameters and they are assumed to have constant values during the machining operation. Other components that are considered in the computation of the machining time are the Initialization, tool change and set-up times, which are included in the total machining time. The summation of PMis from all the machining operations makes up the total PMi of the design scenario.

Computation of the Lubricant and Coolant Consumption impact

The following assumptions are taking into consideration for the lubricant and coolant consumption:

From Table 4.2 CO_2 equivalent emissions:
Lubricant production = 0.469 kg-CO_2/l
Lubricant disposal = 0.0029 kg-CO_2/l
Coolant production = 0.9776 kg-CO_2/l
Coolant disposal = 0.0029 kg-CO_2/l
Water production = 0.189 kg-CO_2/l

Coolant Assumptions:
Initial coolant quantity = 18 liters
Coolant replenishment quantity = 9 liters
Total amount of water = 30 liters
Mean time to replenish coolant = 2 months

Lubricant Spindle Assumptions:
Discharge rate = 0.03 ml
Mean interval between discharge = 480 sec

Lubricant Slideway Assumptions:
Mean interval between supply = 6 months
Lubricant oil quantity supplied = 500 ml

Using equation 4.6 to compute the coolant consumption (Ci) the total machining time is applied:

$$Ci = \left[\left(LCI(cp) + LCI(cd)\right)x\,Tc \; + \; LCI(w)x\,Tw\right]x\,\frac{Mt}{MTTR}$$
$$Ci = [(0.9776 \; + \; 0.0029)x\;(18 + 9) + \; 0.189\;x\;30]x\;\left(\frac{457.02}{5184000^{*}}\right)$$
$$Ci = \; 0.0028\;kg - CO_2$$

*Note: 2 months = 5,184,000 secs

And from equation 4.7 to compute the lubricant consumption (Li) combining both for slideway and spindle we get:

$$Li = \frac{Mt}{MTTD}x\;Ld\;x\;\left(LCI(lp) + \; LCI(ld)\right)$$

$$Li = \left(\left(\frac{457.02}{480}\right)x\;0.00003 + \;\left(\frac{457.02}{15552000\,*}\right)x\;0.5\right)x\;(0.469 + 0.0029)$$

$$Li = 2.041e^{-5}kg - CO_2$$

*Note: 6 months = 15,552,000 secs

Computation of chip waste impact

The stock material is assumed to be initially cut with allowance material and that facing and profile end milling is performed to remove the product with the excess material. The following assumptions were considered in the computation of the chip waste impact:

Material recovery impact for Aluminum = 0.0634 kg-CO_2/kg
Aluminum density = 2.7g/cm^3
Workpiece size = 6mm x 100mm ϕ
Workpiece volume = 47123.88 mm^3
Product volume = 25560.38 mm^3

Using equation 4.8 to compute the chip waste impact (Chi), we get:

$$Chi = (WpV - PV)\;x\;d\;x\;LCI(m)$$
$$Chi = (47123.88 - 25560.38)x\;2.7e^{-6}\;x\;0.0634$$
$$Chi = 0.00369\;kg - CO_2$$

This case study also considers similar assumptions in terms of workpiece size for Grey Cast Iron and Plain Carbon Steel. The other assumptions for Grey Cast Iron and Plain Carbon Steel are as follows (Geoffrey Boothroyd et al., 2010):

Grey Cast Iron density = 7.1 g/cm3
Material recovery impact for Grey Cast Iron = 0.055 kg-CO_2/kg
Plain Carbon Steel density = 7.87 g/cm3
Material recovery impact for Plain Carbon Steel = 0.052 kg-CO_2/kg

Computation of potential Environmental Impact:

The potential environmental impact (Ei) is the summation of all impacts demonstrated in this case study. In the case of machining power consumption impact (PMi), it has to be computed for all the manufacturing processes using the same method as presented in the computation of the impact during the facing operation. Inserting all the computed values and the PMi for all machining processes, we get:

$$Ei = PMi + Ci + Li + Chi$$
$$Ei = 0.273 + 0.0028 + 2.041e^{-5} + 0.00369$$
$$Ei = 0.2803\ kg - CO_2$$

5.2.3 Cost Assessment

The second objective is the minimization of cost. This includes the cost of the material, machining costs and an arbitrary fixed cost to represent the overhead costs. However, after machining, some profit will be gained from selling the chips generated for recycling. The prices of the stock material cost and the recycling profit are dependent on the type of material. The following assumptions are taken into consideration:

Material Cost = Stock price ($/kg) + Stock cutting cost ($/pc)
If the stock size for the design is half, the Stock cutting cost is 50% higher than the whole stock used because it would require a secondary cutting operation to cut it the pieces into half.
Variable Cost = Machining time (hr) x Machining cost per hour ($/hr)
Fixed Cost = overhead cost
Profit from Recycling = Weight of chips generated (kg) x Material recovery gain ($/kg)
Stock price (Aluminum) = $5.28/kg
Stock cutting price = $1/pc
Material Recovery gain (Aluminum) = $5/kg
Machining cost = $10/hr
Fixed cost = $100
Number of units to be machined = 1000 pcs.

The number of units to be machined is necessary to be included in the computation of costs because the amount of stock material and the number of pieces to be cut is a varying factor. This is related to the thickness of the product, which means that an increase in its thickness would result to the increase in the number of stock material to be used. Allowances for the stock material are also considered since at least 20 cm of the stock material is not actually used as workpiece material but rather only to be clamped to the machine during the stock cutting process. Given this, the number of stock material (aluminum tube) is to be computed based on the Stock material assumptions:

Stock diameter = 100 mm
Stock length = 300 mm
Workpiece thickness required = 6 mm (at least, but not recommended)
Stock price for Aluminum = $5.28/kg
Material recovery price for Aluminum = $5/kg

Considering the allowances, a stock length of 300 mm, could produce 46 pcs. of workpiece material 6mm. Therefore, 22 pieces of material stock are needed to produce 1000 pcs. of the product. Given the density of aluminum of 2.7g/cm^3 and the dimensions of the stock material, the weight of one piece of aluminum tube stock material would be 6.36 kg.

Therefore, the total cost of the machining process is the profit from the material gain subtracted from the summation of the costs. This can be defined as (Equation 5.1):

$$Material\ Cost = \frac{\$5.28}{kg} x \frac{6.36kg}{pc} x\ 22pcs + \frac{\$1}{pc} x\ 1012pcs *$$
$$Material\ Cost = \$1750.97$$

*Note: 22 pcs of Stock x 46 pcs/Stock produces 1012 pcs. of workpiece material

$$Variable\ Cost = \frac{0.1602hr}{pc} x\ 1000pcs\ x \frac{\$10}{hr}$$
$$Variable\ Cost = \$1620$$

$$Profit\ from\ Recycling = (47123.88 - 25560.38)mm^3\ x \frac{2.7e^{-6}kg}{mm^3} x \frac{\$5}{kg}$$
$$Profit\ from\ Recycling = \$291.10$$

$$Total\ Cost = Material\ Cost + Variable\ Cost + Fixed\ Cost - Profit\ from\ Recycling \quad (5.1)$$
$$Total\ Cost = 1750.97 + 1620 + 100 - 291.10$$
$$Total\ Cost = \$3162.71\ for\ 1000\ pcs\ or \frac{\$3.16}{pc}$$

The case study also considers similar assumptions in terms of Stock dimensions for Grey Cast Iron and Plain carbon steel. . The other assumptions for Grey Cast Iron and plain carbon steel are as follows (Geoffrey Boothroyd, et al., 2010):

Stock price for Grey Cast Iron = \$0.286/kg
Material recovery price for Grey Cast Iron = \$0.143/kg
Stock price for Plain Carbon Steel = \$0.99/kg
Material recovery price for Plain Carbon Steel = \$0.495/kg

5.2.4 Weight Assessment

The third objective of the problem is to have a minimum weight of the cam assembly. The main parameter that greatly influences the weight is obviously the type of material to be used. Another parameter to take note is the stock size. Using a whole disk for the cam hinders the cam plate to have a light weight, but does not require screws and a back plate to keep it in place. On the contrary, using half of the disk as a workpiece material reduces half of the weight of the stock, but as a trade-off requires a back plate and some screws, which also add to the weight. The assembly weight is computed using the formula in equation 5.2. The following assumptions are considered:

Screw weight = 1.4 g or 0.00014 kg
Shaft weight = 0.05 kg
Back plate weight = 0.02 kg

$$Assembly\ Weight = Product\ Weight + Screw\ Weight\ x\ no.of\ screws + shaft\ Weight + back\ plate\ Weight \quad (5.2)$$
$$Assembly\ Weight = 0.069kg + 0.05kg$$
$$Assembly\ Weight = 0.119kg$$

In summary, the objectives of the product design are possible to be evaluated numerically. These serve as the fitness functions that the chromosomes have to satisfy which leads to finding the best solution. The three functions are assumed to have equal priorities and thus, each criterion contributes 33.33% to the design assessment.

5.3 Generation and Selection of Optimized design using GA

All the design parameter limitations and fitness functions with their corresponding assumptions are all encoded in Excel, where if one changes the values in the designated cells for the design parameter will immediately show its potential environmental impact, cost and assembly weight. Using the GanetXL add-in automatically generates the population for GA, automatically substituting chromosomes in the designated cells where the parameters are entered, and the values of the evaluated objectives (fitness functions) are recorded. This action is performed individually until the terminating criterion is satisfied. Using the following assumptions in GA, the search results of finding the optimum solution that satisfies the criteria are shown in Table 5.4.

Population size = 50
Cross-over method = Simple one point
Cross-over rate = 95%
Mutator = Simple by gene
Mutation rate = 5%
Selector = crowded tournament
Number of generations = 100
No. of genes = 10
Objectives (Multi-objective method):

- Minimize Environmental Impact
- Minimize Cost
- Minimize Weight

Gene Type = Integer Bounded numbers

Table 5.4 Gene value limitation

Parameter	Gene number	Lower Limit	Upper Limit
Material	G0	1	3
Profile cut	G1	1	2
Stock size	G2	1	2
offset	G3	3	5
screw_diameter	G4	2	7
no_of_screws	G5	1	6
no_of_pockets_upper	G6	0	4
no_of_pockets_lower	G7	0	4
fillet	G8	3	15
thickness	G9	3	7

Given the population size of 50 leads to the result of 50 chromosomes found as the optimum solution in the GA run. These 50 individuals are considered as the 50 best designs in the Pareto optimal and they are considered mathematically equally good solutions. Among these solutions, the designers have the freedom to choose which design would satisfy them, since the criteria have already been satisfied. The design can be reconfigured directly from the Excel file through the design tables in Solidworks.

The resulting top designs consists 88% of the designs made from Aluminum material, while, 10% are made from Steel and 2% from Cast Iron. Aluminum is the most favorable material because firstly, it is the lightest material among them, secondly because it has the highest profit return per kg of waste generated and its material properties allows it to be machined at a high rpm and feed rate, which makes it faster to be machined, having a lower machine time. However, it may still not be the only best solution, because Aluminum is also the most expensive material, which contradicts the cost objective.

Just looking at the design objectives individually, there are specific design solutions that satisfy just one criterion. For example using the ranking method, chromosome ID 4834 highlighted in blue from Table 5.5 is the best design, if only the environmental impact is taken into consideration because it has the lowest value of Environmental Impact. For the cost objective, chromosome 283 is the best design, while chromosome 2163 is the best design if only the weight objective is to be satisfied.

The selection method to identify which is the optimum design for this multi-objective problem is the weighted average method, which requires knowing the highest and lowest values from the list of each objective. With the assumption of a 33.33% equally distributed weight priority of each objective, chromosome 610 highlighted in yellow is the resulting best design.

Table 5.5 Results of the search for the optimum design using GA

ID	G0	G1	G2	G3	G4	G5	G6	G7	G8	G9	EI	Cost	Wt.	Wt. ave.
610	1	2	2	4	2	1	0	0	3	3	0.070888	1916.726	0.109419	0.111758
4969	1	2	1	5	6	5	0	1	15	3	0.069623	2236.433	0.096004	0.153134
4834	1	2	1	5	6	1	0	0	3	3	0.067748	2238.334	0.097805	0.155257
5032	1	2	1	3	7	1	0	0	3	3	0.067877	2238.653	0.097722	0.155309
594	1	2	2	4	7	3	1	0	3	3	0.096871	2051.932	0.107073	0.171139
1532	1	2	2	4	2	1	0	1	14	3	0.099183	2060.796	0.106278	0.174354
182	1	1	2	3	2	1	0	0	3	3	0.111746	2094.685	0.098884	0.181528
3582	1	2	1	3	7	1	1	1	15	3	0.084931	2319.203	0.09467	0.188945
866	1	1	2	4	5	5	0	0	11	3	0.110752	2105.658	0.101984	0.189845
4019	1	2	1	3	6	4	1	4	15	3	0.086139	2322.875	0.094486	0.190932
1464	1	2	1	3	7	6	1	0	15	3	0.087807	2327.456	0.093812	0.192604
3825	1	2	1	4	7	6	1	2	15	3	0.087805	2327.612	0.093843	0.192709
4710	1	1	1	3	7	1	0	4	3	3	0.094208	2360.95	0.092434	0.205449
2656	1	1	1	4	7	1	0	0	3	3	0.092761	2358.874	0.093588	0.205736
4993	1	1	1	3	7	4	0	0	4	3	0.096373	2368.285	0.091889	0.208696
4901	1	1	1	3	7	6	0	0	3	3	0.097083	2369.203	0.091575	0.209109
4539	1	1	1	3	7	3	0	0	11	3	0.099375	2384.086	0.091468	0.215255
5038	1	1	1	3	7	3	0	1	15	3	0.101995	2394.472	0.090586	0.219023
1745	1	1	1	3	7	6	0	0	15	3	0.10372	2399.424	0.090071	0.221218
516	1	1	2	3	6	4	1	0	7	3	0.137729	2229.891	0.096539	0.240909
2001	1	1	1	3	7	6	1	0	3	3	0.114041	2457.273	0.090027	0.247786
2668	1	1	1	3	7	6	1	0	8	3	0.116404	2469.471	0.08976	0.253041
5019	2	2	1	3	6	1	0	0	15	3	0.069592	2171.105	0.146394	0.253056
1379	2	2	1	3	2	1	0	0	15	3	0.069521	2171.018	0.146987	0.254299
2393	1	1	1	3	7	6	1	2	11	3	0.118058	2477.108	0.089405	0.256127
4319	1	1	1	3	7	3	1	0	15	3	0.118953	2482.542	0.089038	0.257699
4337	2	2	1	3	2	1	0	0	12	3	0.069413	2172.049	0.149071	0.259151
1073	1	1	1	3	7	6	1	0	15	3	0.120679	2487.494	0.088523	0.259895
2596	2	2	1	5	2	1	0	0	3	3	0.069293	2173.188	0.151372	0.26451
1211	1	1	1	3	7	6	2	0	3	3	0.136262	2575.25	0.088446	0.300079
1226	1	1	1	3	7	6	2	0	8	3	0.138625	2587.449	0.088179	0.305334
4980	1	1	1	3	7	1	2	2	15	3	0.140024	2597.218	0.0878	0.308529
3256	1	1	1	3	7	6	2	0	12	3	0.140883	2597.671	0.087656	0.309415
1693	1	1	1	3	7	6	2	3	15	3	0.1429	2605.471	0.086942	0.312188
283	3	2	2	5	2	5	0	0	4	3	0.097993	1754.434	0.20625	0.330431
126	2	2	2	4	5	5	0	0	11	3	0.077287	1806.432	0.223196	0.35431
2910	1	1	1	3	7	6	3	3	12	3	0.160313	2704.281	0.086915	0.357401
2530	1	1	1	3	7	6	3	3	15	3	0.16233	2712.081	0.086201	0.360174
4981	1	1	1	3	7	4	4	1	3	3	0.173393	2775.648	0.086143	0.388986
3868	1	1	1	3	7	6	4	0	4	3	0.174984	2781.333	0.08577	0.391502
3944	1	1	1	3	7	6	4	3	8	3	0.176906	2791.148	0.085533	0.395705
4543	1	1	1	3	7	4	4	3	15	3	0.18003	2805.869	0.084639	0.401096
1962	1	1	1	3	7	6	4	3	15	3	0.18118	2809.17	0.084296	0.402559
1786	1	1	2	3	4	1	0	4	3	3	0.224924	2670.966	0.08632	0.431911
413	1	1	2	3	4	1	2	3	7	3	0.247725	2794.507	0.085167	0.487215
3352	1	1	2	3	6	4	1	4	15	3	0.250906	2806.172	0.083974	0.491291
1848	1	1	2	3	4	1	2	4	3	3	0.27602	2938.577	0.082026	0.549811
2262	1	1	2	3	7	6	4	3	15	3	0.294672	3043.255	0.08175	0.597404
3266	1	1	2	3	7	6	3	4	3	3	0.296983	3052.12	0.080954	0.600619
2163	1	1	2	3	5	1	4	4	15	3	0.322966	3187.325	0.078608	0.66

Table 5.6 Design Scenarios of the best designs

Chromosome 4834: Least Environmental Impact Material: Aluminum		Impact: 0.067 kg-CO_2 Cost: $2238.33 Weight: 0.097 kg
Chromosome 283: Least Cost Material: Gray Cast Iron		Impact : 0.097 kg-CO_2 Cost: $1754.43 Weight: 0.206 kg
Chromosome 2163: Lightest Weight Material: Aluminum		Impact : 0.322 kg-CO_2 Cost: $3187.32 Weight: 0.078 kg
Chromosome 610: Optimum Solution Material: Aluminum		Impact : 0.071 kg-CO_2 Cost: $1916.72 Weight: 0.109 kg

5.4 Interpretation of Results

As mentioned in chapter 4, multi-objective optimization problems, have no single solution that exists which is the optimum solution to all the objectives given. In this particular case study, the objectives are directly influenced by the design parameters, but conflicting objectives causes the results to move towards the opposite ends of the scale. Trade-offs has to be made and best solutions are in the range of the Pareto optimal area of the solution space. Visualizing the Pareto optimal frontier of a multi-objective optimization problem is possible using a display of bi-objective cross sections of the Pareto optimal frontier. These “slices” of the Pareto optimal frontier are called Decision maps, which are introduced by W.S Meisel in 1972. Figures 5.3-5.5 shows the Pareto optimal frontier, where each graph shows the contrast between two objectives.

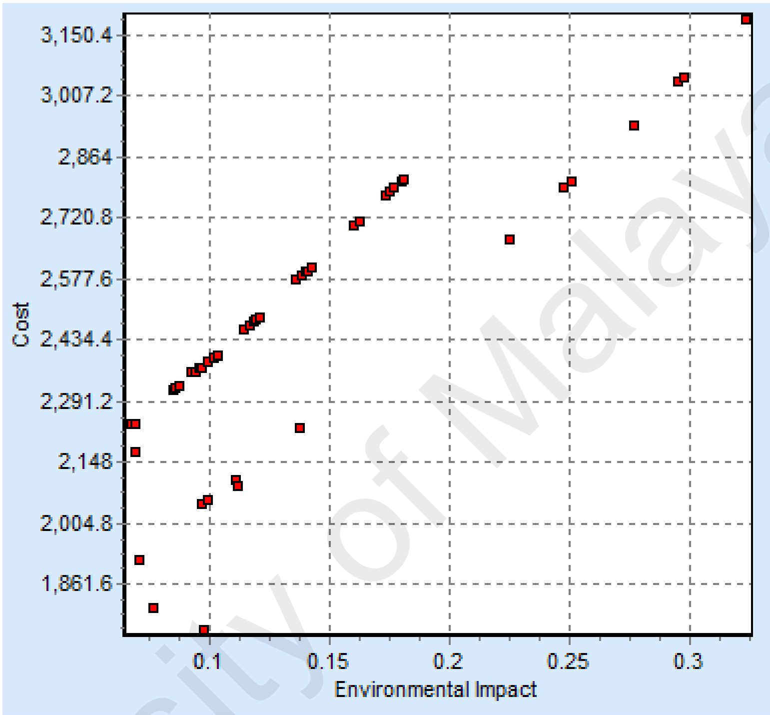


Figure 5.3 Solution space of Cost vs. Environmental Impact

In Figure 5.3, the resulting solutions show a seemingly linear relationship between cost and environmental impact, where the cost increases as the environmental impact increases. This is influenced by the machining time, which both objectives use as basis for the computation of their values.

The solutions also show 2 parallel lines, and according to the analysis of data, the solutions are divided due to the G2 parameter, or the stock size parameter. The solutions belonging to the higher cost line all have a half stock size, compared to the solutions in the lower cost line, which have whole stock size. It shows that it is more expensive to use the half design stock size because of the additional cost to cut the stock into half. However, it will not have an effect on the environmental impact of the machining process because the features being machined would be similar.

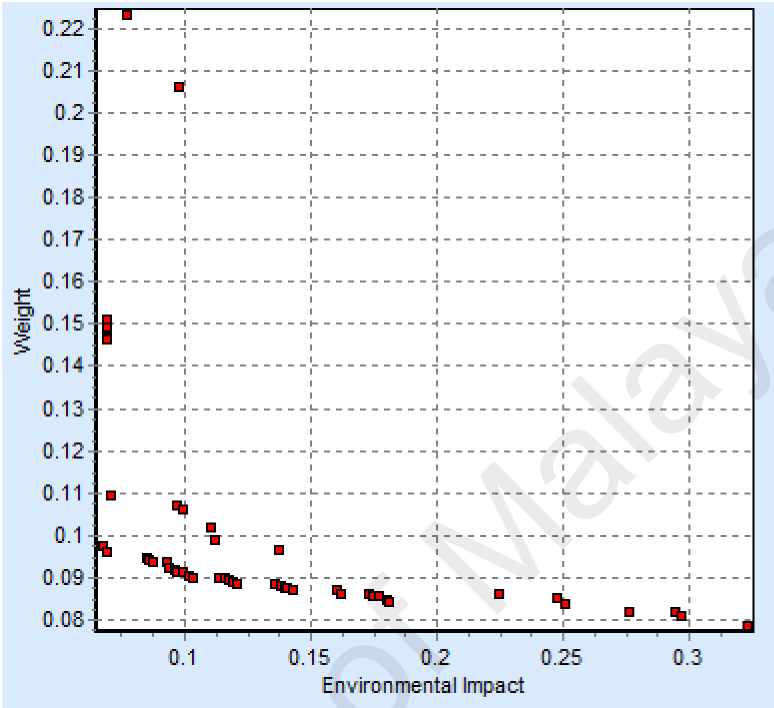


Figure 5.4 Solution space of Weight vs. Environmental Impact

Figure 5.4 shows an interesting contradiction of objectives Weight and Environmental Impact. The outlier solutions above the 0.14 kg weight objectives are Cast Iron and Steel, which even with a heavier weight among the other solutions, are still considered as good solutions due to their low environmental impact. On the other hand, the Aluminum solutions on the lighter weight range show a contradicting relationship where the environmental impact increases as the weight decreases. The lighter products has more material taken out of the stock material, which means they had longer machining time, more power consumed and waste generated.

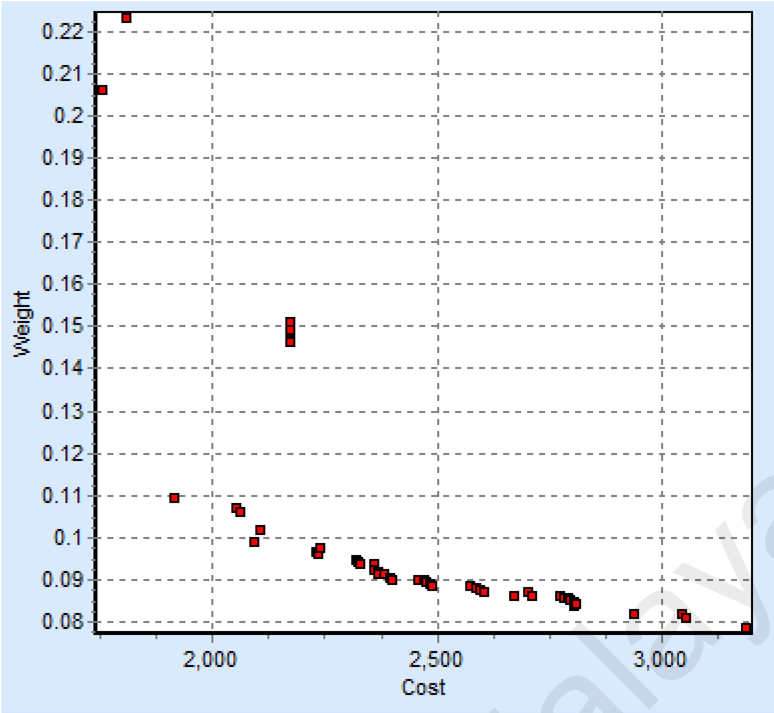


Figure 5.5 Solution space of Cost vs. Weight

Similarly, Figure 5.5 shows a trade-off between cost and weight objectives. The outlier solutions above the 0.2 kg scale are Steel and Cast Iron, which are the cheapest. The next cluster of solutions which are in the 0.15 kg weight range are the rest of the Steel solutions. The lone 0.22 kg Steel, which is the heaviest among the population, has a whole stock size configuration, which is the reason for its low cost. The rest of the Steel solutions have a half stock size, which contributes to their higher cost. The Aluminum solutions show a contradicting relationship between Cost and Weight, where the lighter weight would lead to higher cost. This is due to the material properties of aluminum, which is the lightest among the materials, and also the most expensive. Another reason is similar to the contrast of weight and environmental impact, where the lightest material would have more material taken out, thus longer machining time, which also correlates to cost. Looking at this graph outright, it is tempting to say that the best solution would be in the area of the Steel half stocks with the approximately 0.15 kg weight. Visually, it seems that they are in the middle of the cost and weight graph and one can easily see that it is not too expensive and not too heavy. Depending on the requirement, designers are not limited to a single design result, which can still stretch their technical capabilities to higher level of decision making.

5.5 Chapter Summary

The case study presented demonstrates the proposed method, which incorporates the consideration of environmental impact specifically in the manufacturing stage of the product. This method can be adapted to the current design methodologies of Malaysian design firms, which do not include environmental consideration as a part of their design selection criteria (Sakundarini, et al., 2010). The novel combination of Feature-based design and Life Cycle Inventory to assess the environmental impact of a specific design provides a detailed evaluation of the product based on the amount of resources consumed and waste produced. The use of Genetic Algorithm suits the representation of each feature as a gene that needs to be optimized collectively with the other features. It offers a quick solution in finding the optimum solutions based on the given fitness functions. Such a semi-automated design approach is suitable to be incorporated to the current design methodologies because it does not require the designer to conduct further study on environmental impact assessment and optimization methods, which may be a possible additional burden to their current tasks. The next chapter focuses on how this proposed method compares to the existing methods which are being used by designers.

CHAPTER 6

VALIDATION

6.1 Introduction

In chapter 3, the framework of the research has taken shape and became the basis of the flow of this dissertation. Following the application of the proposed model in a case study is its validation. The purpose of the validation process is to assess the quality of the proposed method in terms of comparison to existing established methods. Through the validation process, it contributes an increase in understanding of the important parameters taken into consideration during the design of the proposed integrated design solution framework. This leads to the refinement of the proposed model.

The next section presents the methodologies for each validation focus, in which the structure was initially introduced in Chapter 3. There are three aspects, which the proposed model is compared with. First, with actual machining experiments through direct measurement; Second, with an established optimization method; And last, with an existing CAD Environmental Assessment tool. In the final sections of this chapter, the comparative results are analyzed and conclusions are drawn.

6.2 Comparison with Experimental results

The goal of this validation is to ascertain the validity of the forecasted power consumption using the proposed method. Using the resulting optimum product solutions from the case study performed, the proposed method is validated through actual machining of the products using a CNC machine. Based on the discussion of the case study results, the biggest contributing factor to the environmental impact in machining processes is the power consumption. This is primarily based from the product's machining time, and the spindle speed of the machine. For this validation, the forecasted power consumption using the proposed method is contrasted with the actual power consumption from the measured experiment of machining the same product design and using the same parameters for machining.

Table 6.1 Comparison of the actual machining power consumption with the forecasted power consumption in Designs with (a) Least Environmental Impact (b) Least Cost (c) Lightest Weight (d) Optimum solution

a) Least Environmental Impact Design

Machining Process	Actual Machining (W)	Proposed (W)	% Difference
Facing	3.743	7.360	65%
Drilling	0.146	0.899	144%
Drilling screw	0.155	0.392	87%
Slot Machining	6.176	21.415	110%
Fillet R	0.325	0.919	95%
Fillet L	0.323	0.919	96%

b) Least Cost Design

Machining Process	Actual Machining (W)	Proposed (W)	% Difference
Facing	43.526	22.505	64%
Slot machining	9.398	30.508	106%
Drilling	0.327	0.899	93%

c) Lightest Weight Design

Machining Process	Actual Machining (W)	Proposed (W)	% Difference
Facing	12.824	14.721	14%
Drilling	0.114	0.910	156%
Slot Machining	6.269	21.415	109%
Lower Pocket 1	8.218	16.989	70%
Upper Pocket 1	5.984	15.336	88%
Upper Pocket 2	4.806	11.400	81%
Lower Pocket 4	8.208	16.989	70%
Lower Pocket 2	8.160	16.989	70%
Lower Pocket 3	8.230	16.989	69%
Upper Pocket 3	4.154	14.606	111%
Upper Pocket 4	5.908	15.336	89%
Profile	5.874	8.100	32%

d) Optimal Design

Machining Process	Actual Machining (W)	Proposed (W)	% Difference
Facing	13.306	14.721	10%
Slot machining	6.339	21.415	109%
Drilling	0.313	0.910	98%

The high percentage difference between the actual machining power consumption and the forecasted power consumption using the proposed method led to the assumption that the power profile that was used in the proposed method, which was the power profile from the experiments conducted by Arakawa (2007) with a Makino V33 Milling Machine, does not correspond to the machine used in the machining experiments. A new power profile for the Makino KE55 Milling Machine is taken for the Spindle motor and the feed motors for x, y, and z axis using the Power & Harmonics Analyzer. The power profile was generated by taking the power measurements for varying levels of spindle motor and feed motor speed. Figure 6.1and Figure 6.2 show the power profiles for the spindle motors of the Makino KE55 and the Makino V33 (adopted from (Arakawa & Aoyama, 2007)) respectively. Additionally, Figure 6.3 and Figure 6.4 show the power profiles for the feed motors.

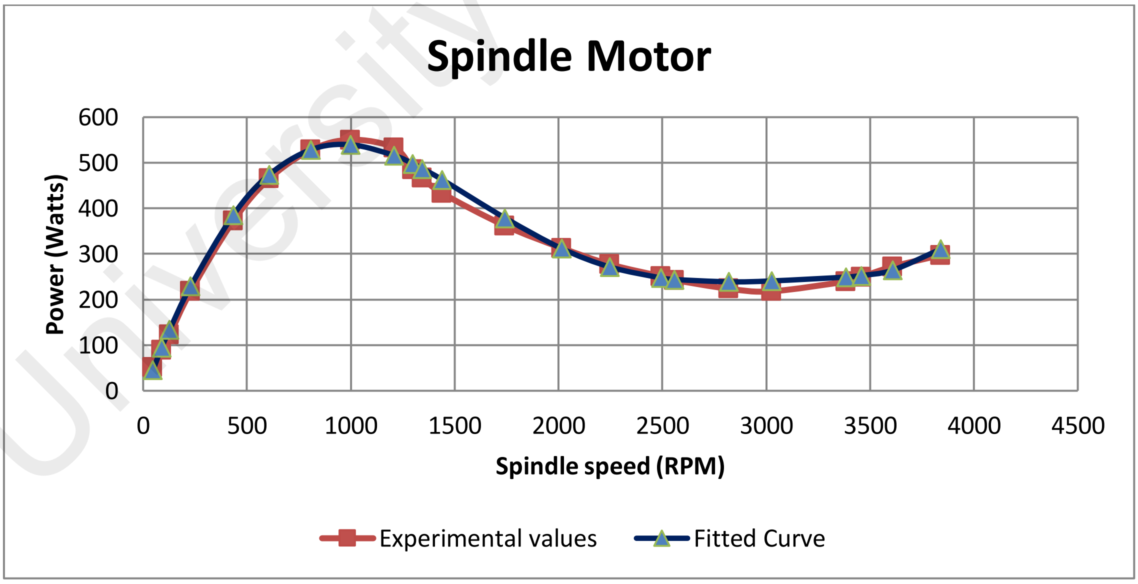


Figure 6.1 Power profile of the Makino KE55 Spindle motor

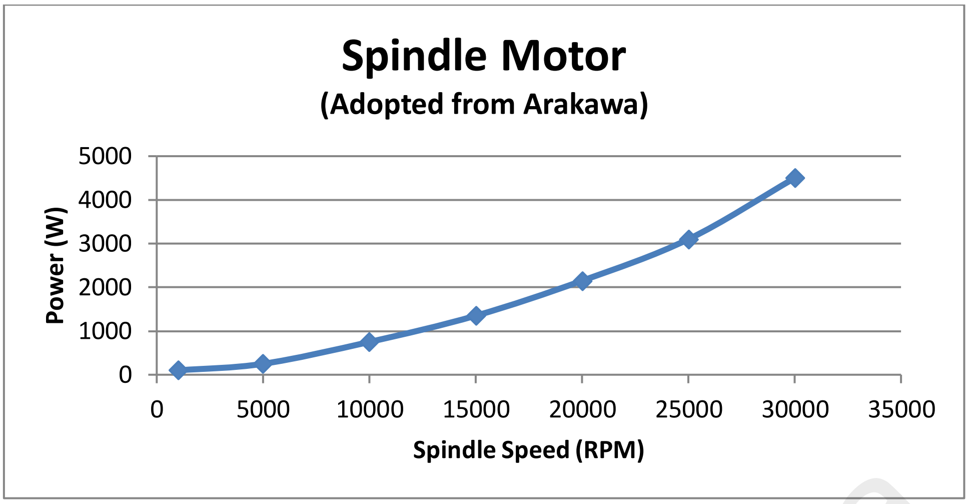


Figure 6.2 Power profile of the Makino V33 Spindle motor adopted from (Arakawa & Aoyama)

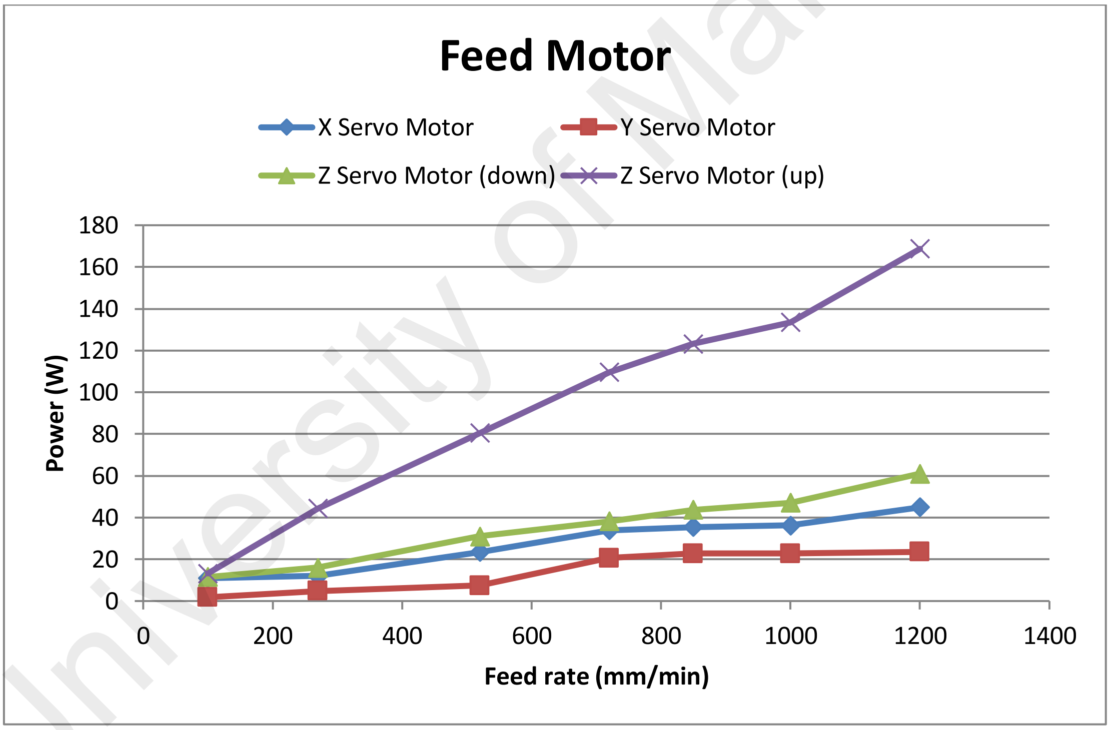


Figure 6.3 Power profile of the Makino KE55 feed motor

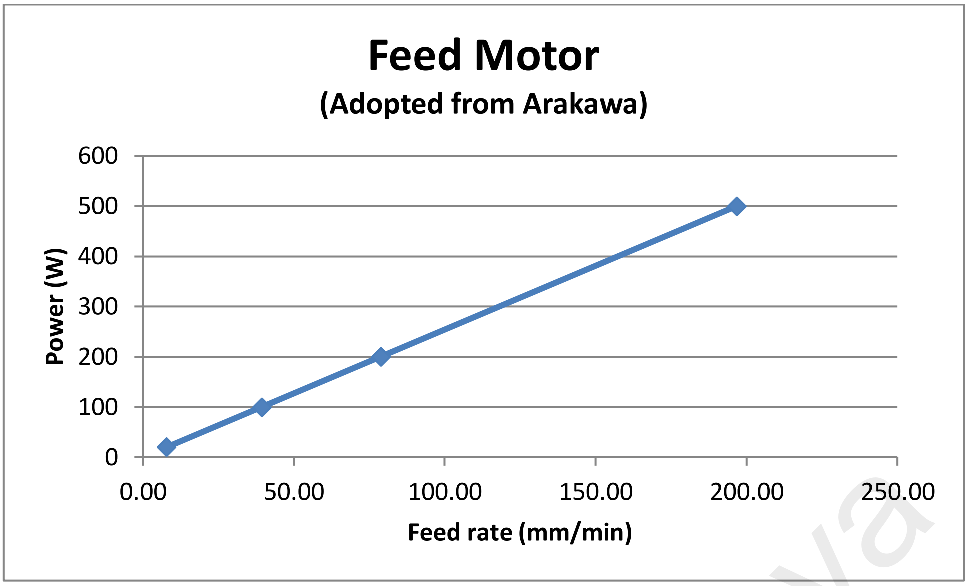


Figure 6.4 Power profile of the Makino V33 Feed drive motor adopted from (Arakawa & Aoyama, 2007)

Based on the power profile of the Makino V33, it seems safe to assume a linear relationship between the spindle motor power and the spindle speed. This may be true in cases with high spindle speed. However, this is not the case particularly for the lower range of the spindle speed spectrum. Figure 6.1 plots the power consumption data points gathered in varying speeds, which resulted to a polynomial curve. Using curve fitting functions allows us to find the equation of the curve:

$$y = 9.1180E - 18x^6 - 1.0544E - 13x^5 + 4.2636E - 10x^4 - 5.9056E - 7x^3 \quad (6.1)$$
$$-2.9593E - 4x^2 + 1.0960x - 6.4875$$

In the case of the feed motor, it is safe to assume a linear relationship between the power and the feed rate. However, the z-axis feed motor displays different sets of data for each direction of movement. Due to the additional weight of the work table that needs to be lifted during vertical machining operations (drilling, boring, etc.), the z-axis feed motor requires higher power consumption, thus a higher slope value to its linear equation.

$$\text{x-axis: } y = 0.0308x + 7.875 \quad (6.2)$$

y-axis: $y = 0.0197x - 0.18$ (6.3)

(-) z-axis: $y = 0.045x + 7.001$ (table down direction) (6.4)

(+) z-axis: $y = 0.1413x - 0.904$ (table up direction) (6.5)

Replacing the power profile from Arakawa's data with the new power profile gathered from the experiments to the proposed method, the new percentage difference between the power consumption of the proposed method and the actual experiments are greatly decreased, as shown in Table 6.2. Some machining processes with a significantly high percentage difference can be attributed to the +/- 1 Watt (+/-0.001 KW) error of the Power Analyzer measuring device. Given these circumstances, the assumptions used in the proposed method is comparable to the actual machining scenario, given that the power profile is specific to the machine to be used.

Table 6.2 Comparison of the actual machining power consumption with the forecasted power consumption in Designs with (a) Least Environmental Impact (b) Least Cost (c) Lightest Weight (d) Optimum solution using the Makino KE55 profile

a) Least Environmental Impact Design

Machining Process	Actual Machining (W)	Proposed (W)	% Difference
Facing	3.743	4.979	28%
Drilling	0.146	0.143	2%
Drilling screw	0.155	0.145	6%
Slot Machining	6.176	8.029	26%
Fillet R	0.325	0.347	7%
Fillet L	0.323	0.347	7%

b) Least Cost Design

Machining Process	Actual Machining (W)	Proposed (W)	% Difference
Facing	43.526	37.658	14%
Slot machining	9.398	11.742	22%
Drilling	0.327	0.245	29%

c) Lightest Weight Design

Machining Process	Actual Machining (W)	Proposed (W)	% Difference
Facing	12.824	12.715	1%
Drilling	0.114	0.107	6%
Slot Machining	6.269	8.029	25%
Lower Pocket 1	8.218	8.174	1%
Upper Pocket 1	5.984	6.971	15%
Upper Pocket 2	4.806	5.012	4%
Lower Pocket 4	8.208	8.174	0.4%
Lower Pocket 2	8.160	8.174	0.2%
Lower Pocket 3	8.230	8.174	1%
Upper Pocket 3	4.154	3.350	21%
Upper Pocket 4	5.908	6.971	17%
Profile	5.874	4.928	18%

d) Optimal Design

Machining Process	Actual Machining (W)	Proposed (W)	% Difference
Facing	13.306	12.715	5%
Slot machining	6.339	8.029	24%
Drilling	0.313	0.287	9%

6.3 Comparison with Taguchi method

The goal of this validation is to demonstrate the validity of GA in the proposed method in terms of producing an optimum solution by comparing it to an already established product design optimization method. According to (Rajkumar Roy, et al., 2008), the mostly used design optimization methods in the industry are expert-based and design of experiments based optimization. Due to this, the results of the case study are compared to the results of the same case study using Taguchi method, which is a type of DOE-based optimization.

Since the basic Taguchi method is a single objective optimization method, the product will undergo the Taguchi optimization method 3 times, one for each criterion to be satisfied, which are the design with the least environmental impact, least cost and lightest weight. Given that 10 design parameters each with up to 3 levels are to be optimized, an orthogonal array of 18 design scenarios is used for each analysis. The levels of each parameter are represented as per Table 6.3.

Table 6.3 Parameter Level representation of the case study

		Level		
		1	2	3
Parameters	A = Material	Alum	Steel	Cast Iron
	B = Profile cut	Yes	No	-
	C = Stock size	Half	Whole	-
	D = offset	3	4	5
	E = screw_diameter	2	4	6
	F = no_of_screws	1	3	5
	G = no_of_pockets_upper	0	2	4
	H = no_of_pockets_lower	0	2	4
	I = fillet	3	8	13
	J = thickness	3	5	7

Table 6.4 Orthogonal Array L18 representation for the case study

Expt.	A	B	C	D	E	F	G	H	I	J
1	1	1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	1	2	2	1	2
3	1	1	1	3	3	2	3	2	3	3
4	2	1	2	1	1	2	2	3	3	1
5	2	1	1	2	2	3	3	3	1	2
6	2	1	2	3	3	3	1	2	2	3
7	3	1	1	1	2	2	3	1	3	1
8	3	1	2	2	3	2	1	3	3	2
9	3	1	1	3	1	3	2	2	2	3
10	1	2	2	1	2	3	2	2	1	1
11	1	2	1	2	1	1	3	3	2	2
12	1	2	2	3	3	1	1	1	3	3
13	2	2	1	1	2	1	1	2	2	1
14	2	2	2	2	3	2	2	1	1	2
15	2	2	1	3	1	2	3	3	1	3
16	3	2	2	1	2	3	3	2	2	1
17	3	2	1	2	1	3	1	1	3	2
18	3	2	2	3	3	2	2	3	2	3

Each of the design scenario's (Expts. 1-18) environmental impact, cost and weight are computed based on their specific design parameters. The values from the assessment come from the assessment part of the proposed method by plugging in the respective design parameters of each experiment. The signal to noise ratio (S/N) helps in the analysis and prediction of optimum parameters. The optimization involves determining the best level for each parameter so that the value of the criteria reaches its target value. In this particular case study, the type of S/N (η) ratio used is the "smaller the better" form. This is usually chosen if the target value for a criterion is zero. This is expressed as:

$$\eta = -10 \log_{10} X \qquad (6.6)$$

where: X = mean of sum of squares of the data

In this case, data refers to the assessment values (environmental impact, cost and weight) since there are no other experimental values (due to the fact that the data comes from assessment, there are also no noise factors to be considered), the value of X will just be the square of the data. As mentioned, each criterion is to be analyzed separately.

6.3.1 Analysis of Environmental Impact Criterion

Each design scenario is assessed using the proposed method and Table 6.5 shows the corresponding Environmental impact and S/N ratio for each design scenario.

Table 6.5 Summary of Calculated Environmental Impact and S/N ratios for the 18 product design scenarios

Expt.	A	B	C	D	E	F	G	H	I	J	Environmental Impact (kg-CO_2)	S/N Ratio (η)
1	1	1	1	1	1	1	1	1	1	1	0.0945	20.488
2	1	1	2	2	2	1	2	2	1	2	0.2489	12.081
3	1	1	1	3	3	2	3	2	3	3	0.2540	11.903
4	2	1	2	1	1	2	2	3	3	1	0.3354	9.488
5	2	1	1	2	2	3	3	3	1	2	0.2336	12.629
6	2	1	2	3	3	3	1	2	2	3	0.2819	10.997
7	3	1	1	1	2	2	3	1	3	1	0.2955	10.590
8	3	1	2	2	3	2	1	3	3	2	0.4041	7.871
9	3	1	1	3	1	3	2	2	2	3	0.3127	10.096
10	1	2	2	1	2	3	2	2	1	1	0.1786	14.964
11	1	2	1	2	1	1	3	3	2	2	0.1764	15.072
12	1	2	2	3	3	1	1	1	3	3	0.0934	20.596
13	2	2	1	1	2	1	1	2	2	1	0.0695	23.155
14	2	2	2	2	3	2	2	1	1	2	0.1372	17.250
15	2	2	1	3	1	2	3	3	1	3	0.2107	13.525
16	3	2	2	1	2	3	3	2	2	1	0.2811	11.022
17	3	2	1	2	1	3	1	1	3	2	0.1033	19.721
18	3	2	2	3	3	2	2	3	2	3	0.3829	8.339
											Mean	**13.87**

The effect of a parameter level is defined as its deviation between the lowest and highest means of S/N (η) ratio per level. This means that the average value of the η for each level and for each parameter has to be considered. For example, the mean of η of Parameter A Level 1 (Material: Aluminum) is the mean of the S/N ratios of Experiments 1-3 and 10-12, which is valued 15.9 dB. A summary of the means of the η for each level of parameter is shown in Table 6.6. The difference between the highest and lowest value is shown in last row.

Table 6.6 S/N responses per level of each parameter

Level	A	B	C	D	E	F	G	H	I	J
1	15.9	11.8	15.2	13.5	15.8	19.6	17.1	18.9	15.5	15.0
2	14.5	16.0	12.5	10.9	15.5	12.1	12.0	12.3	16.1	14.1
3	11.3			11.0	11.9	14.5	12.5	8.6	14.1	12.6
delta	4.6	4.2	2.7	2.7	3.9	7.5	5.1	10.4	2.0	2.4

The goal of this optimization is to identify the best level for each parameter that will yield the lowest potential environmental impact. Since –log depicts a decreasing function (Equation 6.6), we should maximize η. Hence, the optimal level for a parameter is the one with the highest value of η. From Table 6.6, the optimal conditions for each parameter are highlighted. We can conclude that the following design configuration have the least potential environmental impact:

Table 6.7 Predicted Design Scenario with the Least Environmental Impact using Taguchi Method

A	B	C	D	E	F	G	H	I	J
1	2	1	1	1	1	1	1	2	1

Material	Aluminum
Profile cut	no
Stock size	half
offset	3
screw_diameter	2
no_of_screws	1
no_of_pockets_upper	0
no_of_pockets_lower	0
fillet	8
thickness	3

The optimum design predicted does not have a profile cut and its stock size is half. That means that in the actual design, there are no offsets, lower pockets and fillets to be considered. Similarly, these parameters are ignored in the prediction of the potential environmental impact of the optimum design. Given the identified optimum conditions, the value of η is predicted using the additive model as:

$$\eta = \eta_m + \sum_{i=1}^{n}(\eta_i - \eta_m) \qquad (6.7)$$

Where η_m = total mean of the S/N values

η_i = mean of S/N values at optimal level

Therefore, the predicted η for the optimum design:

$\eta = 13.87 + (15.9 - 13.87) + (16 - 13.87) + (15.2 - 13.7) + (17.1 - 13.87) + (15.0 - 13.87)$

$\eta = 23.6\ dB$

Further using Equation 6.6, the predicted environmental impact at optimal conditions:

$$X = \sqrt[2]{10^{\frac{-\eta_{opt}}{10}}} \qquad (6.8)$$

$$X = \sqrt[2]{10^{\frac{-23.6}{10}}}$$

X =0.066 kg-$CO_{2\text{-equiv}}$

6.3.2 Analysis of the Cost Criterion

Again using the proposed method, each design is assessed in terms of its manufacturing cost as defined in Chapter 5. The S/N ratios and their means for each level per parameter were computed and are summarized in Table 6.8 and Table 6.9.

Table 6.8 Summary of the calculated Cost and S/N ratios for the design scenarios

Expt.	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**Cost ($)**	**S/N Ratio (η)**
1	1	1	1	1	1	1	1	1	1	1	2364.30	-67.47
2	1	1	2	2	2	1	2	2	1	2	2968.27	-69.45
3	1	1	1	3	3	2	3	2	3	3	3336.41	-70.47
4	2	1	2	1	1	2	2	3	3	1	3240.59	-70.21
5	2	1	1	2	2	3	3	3	1	2	3088.60	-69.80
6	2	1	2	3	3	3	1	2	2	3	3188.42	-70.07
7	3	1	1	1	2	2	3	1	3	1	3395.16	-70.62
8	3	1	2	2	3	2	1	3	3	2	3512.89	-70.91
9	3	1	1	3	1	3	2	2	2	3	3469.80	-70.81
10	1	2	2	1	2	3	2	2	1	1	2472.48	-67.86
11	1	2	1	2	1	1	3	3	2	2	2844.93	-69.08
12	1	2	2	3	3	1	1	1	3	3	2504.01	-67.97
13	2	2	1	1	2	1	1	2	2	1	2173.97	-66.75
14	2	2	2	2	3	2	2	1	1	2	2231.14	-66.97
15	2	2	1	3	1	2	3	3	1	3	3022.98	-69.61
16	3	2	2	1	2	3	3	2	2	1	2794.34	-68.93
17	3	2	1	2	1	3	1	1	3	2	2241.81	-67.01
18	3	2	2	3	3	2	2	3	2	3	3398.66	-70.63
											Mean	**-69.14**

Table 6.9 S/N responses per level of each parameter

Level	A	B	C	D	E	F	G	H	I	J
1	-68.7	-70.0	-69.2	-69.4	-68.8	-67.8	-68.4	-67.5	-69.0	-68.6
2	-68.9	-68.3	-69.1	-70.1	-69.1	-70.2	-69.3	-69.1	-68.9	-68.9
3	-69.8			-70.4	-70.5	-69.2	-69.7	-70.6	-69.4	-69.9

Thus, the optimal design conditions with the least cost:

Table 6.10 Predicted Design Scenario with the Least Cost using Taguchi Method

A	B	C	D	E	F	G	H	I	J
1	2	2	1	1	1	1	1	2	1

Material	Aluminum
Profile cut	no
Stock size	whole
offset	3
screw_diameter	2
no_of_screws	1
no_of_pockets_upper	0
no_of_pockets_lower	0
fillet	8
thickness	3

The optimum design predicted does not have a profile cut and its stock size is whole. That means that in the actual design, there are no offsets, screws, and fillets to be considered. Similarly, these parameters are ignored in the prediction of the potential environmental impact of the optimum design. Given the identified optimum conditions, the value of η is predicted using Equation 6.7:

$$\eta = -69.14 + (-68.7 + 69.14) + (-68.3 + 69.14) + (-69.1 + 69.14) + (-68.4 + 69.14) + (-68.6 + 69.14)$$

$$\eta = -66.66\ dB$$

Further using Equation 6.8, the predicted cost at optimal conditions:

$$X = \sqrt[2]{10^{\frac{-(-66.66)}{10}}}$$

$X =$\$ 2,153.26 per 1000 pcs.

6.3.3 Analysis of the Weight Criterion

Again using the proposed method, each design is assessed in terms of its weight as defined in Chapter 5. The S/N ratios and their means for each level per parameter were computed and are summarized in and.

Table 6.11 Summary of the calculated Weight and S/N ratios for the design scenarios

Expt.	A	B	C	D	E	F	G	H	I	J	Weight (kg)	S/N Ratio (η)
1	1	1	1	1	1	1	1	1	1	1	0.0927	20.657
2	1	1	2	2	2	1	2	2	1	2	0.1190	18.488
3	1	1	1	3	3	2	3	2	3	3	0.1109	19.099
4	2	1	2	1	1	2	2	3	3	1	0.1433	16.872
5	2	1	1	2	2	3	3	3	1	2	0.1556	16.160
6	2	1	2	3	3	3	1	2	2	3	0.3794	8.417
7	3	1	1	1	2	2	3	1	3	1	0.1113	19.072
8	3	1	2	2	3	2	1	3	3	2	0.2228	13.043
9	3	1	1	3	1	3	2	2	2	3	0.2011	13.930
10	1	2	2	1	2	3	2	2	1	1	0.0988	20.101
11	1	2	1	2	1	1	3	3	2	2	0.1065	19.451
12	1	2	2	3	3	1	1	1	3	3	0.1886	14.487
13	2	2	1	1	2	1	1	2	2	1	0.1504	16.456
14	2	2	2	2	3	2	2	1	1	2	0.3178	9.957
15	2	2	1	3	1	2	3	3	1	3	0.2203	13.138
16	3	2	2	1	2	3	3	2	2	1	0.1695	15.419
17	3	2	1	2	1	3	1	1	3	2	0.1882	14.508
18	3	2	2	3	3	2	2	3	2	3	0.3111	10.141
											Mean	**15.52**

Table 6.12 S/N responses per level of each parameter

Level	A	B	C	D	E	F	G	H	I	J
1	18.71	16.9	16.94	18.9	16.3	18.9	14.59	12.22	16.7	18.1
2	13.5	14.9	14.1	15.9	17.2	17.1	14.91	15.61	16.6	15.26
3	14.35			13.8	19.1	14.9	17.06	13.35	17.6	13.2

Thus, the optimal design conditions with the lightest weight assembly:

Table 6.13 Predicted Design Scenario with the lightest weight using Taguchi Method

A	B	C	D	E	F	G	H	I	J
1	1	1	1	3	1	3	2	3	1

Material	Aluminum
Profile cut	yes
Stock size	half
offset	3
screw_diameter	6
no_of_screws	1
no_of_pockets_upper	4
no_of_pockets_lower	2
fillet	13
thickness	3

The optimum design predicted has a profile cut and its stock size is half. That means that in the actual design, there are fillets, screws, pockets and offsets to be machined. Given the identified optimum conditions, the value of η is predicted using Equation 6.7:

$$\eta = 15.52 + (18.71 - 15.52) + (16.9 - 15.52) + (16.94 - 15.52) + (17.06 - 15.52) + (18.1 - 15.52)$$

$$\eta = 23.18\ dB$$

Further using Equation 6.8, the predicted cost at optimal conditions:

$$X = \sqrt[2]{10^{\frac{-23.18}{10}}}$$

$$X = 0.069 \text{ kg}$$

6.3.4 Comparison of Results

Replacing the resulting optimum conditions to the proposed model, the potential environmental impact, cost and weight of the design are assessed. This is done to verify and compare the predicted values for each criterion. Now comparing the predicted and assessed values of the optimum conditions derived from the Taguchi method with the best designs for each criterion derived from the proposed method using GA as shown in Table 6.14, the GA method is able identify the better design parameters to achieve the desired goals. In addition however, the optimum designs derived from the Taguchi method are within the optimum design results generated by GA, which includes them in the top 50 optimum designs (refer to Table 5.5). Their respective rankings among the GA results are also shown in the Table below.

Table 6.14 Comparison of the optimum design conditions between the Taguchi method and GA

	Optimum Conditions using Taguchi Method		Best Design using Proposed Method (GA)
	Predicted	Using Assessment	
Environmental Impact (kg-$CO_{2\text{-equiv}}$)	0.066	0.072 (8th rank)	0.067 (1st rank)
Cost ($)	2153.26	1916.72 (4th rank)	1754.43 (1st rank)
Weight (kg)	0.069	0.085 (8th rank)	0.078 (1st rank)

The Taguchi method can improve the response of a particular objective by identifying the optimum values for each Level factor. However, it is limited with the amount of level for each factor. Having a wider range of level per factor would mean a larger analysis of data and the possibility of more experiments to be performed. In this validation, the level values for the thickness, fillet, number of pockets, and screw dimensions were fixed values. This means that the search is preformed only among the three factor levels. Unlike in GA, they were represented as a range of values and therefore all values within the range can be used for the search. This given, it is also possible for continuous values to be used when precision of dimensions are required. However, this would be difficult to accomplish using Taguchi method.

6.4 Comparison with Solidworks Sustainability Xpress

The goal of this validation is to compare the results of the environmental impact of the design using the proposed method and the Sustainability Xpress software. However, only the result of the Carbon Footprint indicator during the manufacturing process, Milling, is used in the comparison.

To compare the two methods, different design scenarios used in the Taguchi method validation: Experiments 1 – 18; and the best design scenarios using the proposed method: least environmental impact, least cost, lightest and optimum design, were used in the analysis using the Sustainability Xpress Add-in for Solidworks. The designs scenarios were drawn in CAD and the required parameters: Material and Manufacturing Process, specifically milling process, are entered. The carbon footprint for product's life stages: Material Procurement, Product Manufacturing, Product Use and End of Life are then immediately assessed. Figure 6.5 shows the utilization of Sustainability Xpress Add-in for Solidworks with Experiment 7 design. The necessary inputs, besides the CAD design, are Gray Cast Iron for Material type and Milling for Manufacturing Processes. The specified parameters yielded a 1.76E-003 kg-$CO_{2\ equiv}$ for its impacts during the manufacturing stage.

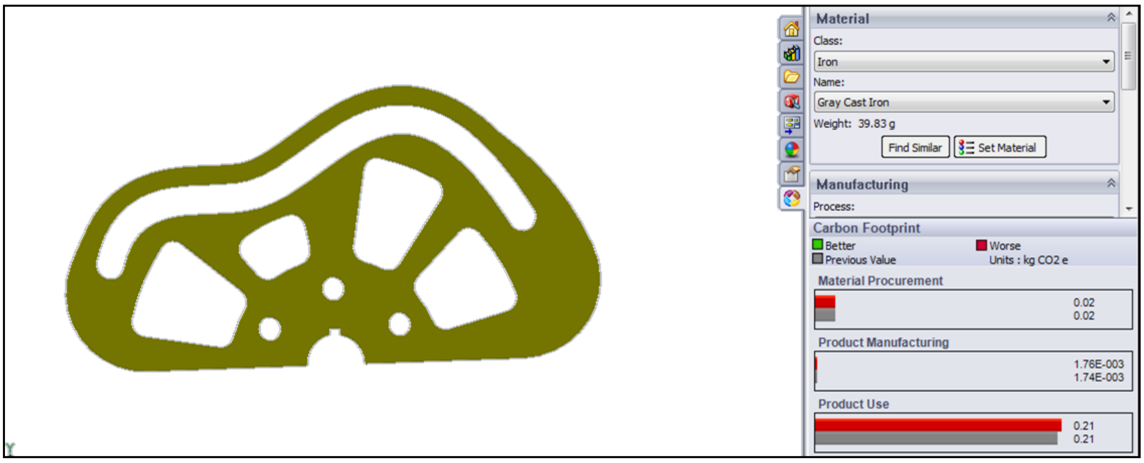


Figure 6.5 Screenshot of Experiment 7 using the Sustainability Xpress tool

Table 6.15 Carbon Footprint (kg-CO_{2equiv}) comparison between Sustainability Xpress and the Proposed method

				Carbon Footprint (Kg-CO2 e)	
Name	**Material**	**Product Volume (mm^3)**	**Material Removed (mm^3)**	**Sustainability Xpress**	**Proposed Method**
exp1	Aluminum	8140	7345.1	0.011	0.095
exp2	Aluminum	25100	21563.5	0.032	0.249
exp3	Aluminum	14400	16414.1	0.019	0.254
exp4	Plain Carbon Steel	12200	19554.4	0.077	0.335
exp5	Plain Carbon Steel	10300	12774.7	0.065	0.234
exp6	Plain Carbon Steel	41000	20970.9	0.257	0.282
exp7	Gray Cast Iron	5540	9953.5	0.002	0.295
exp8	Gray Cast Iron	23900	22791.1	0.008	0.404
exp9	Gray Cast Iron	17400	13043.0	0.006	0.313
exp10	Aluminum	18100	13325.9	0.023	0.179
exp11	Aluminum	13500	10086.2	0.017	0.176
exp12	Aluminum	51300	11482.0	0.066	0.093

exp13	Plain Carbon Steel	10200	5511.8	0.064	0.070
exp14	Plain Carbon Steel	34000	13095.9	0.214	0.137
exp15	Plain Carbon Steel	19000	12367.0	0.120	0.211
exp16	Gray Cast Iron	16800	14591.7	0.005	0.281
exp17	Gray Cast Iron	16600	7013.1	0.005	0.103
exp18	Gray Cast Iron	36800	26051.0	0.012	0.383
Environment	Aluminum	10200	5461.7	0.013	0.068
Cost	Gray Cast Iron	22000	9408.9	0.007	0.098
Weight	Aluminum	11000	20820.2	0.014	0.323
Optimum Design	Aluminum	22000	9408.9	0.028	0.071

Analyzing the results from Table 6.15 Carbon Footprint (kg-CO_{2equiv}) comparison between Sustainability Xpress and the Proposed method shows no relationship between the Carbon Footprint using the Proposed Method and Sustainability Xpress. The Carbon Footprint of the Sustainability Xpress follows a linear relationship to the product's volume as shown in Figure 6.6. This leads to the assumption that GaBi, the LCA software used by Sustainability Xpress, simply uses an LCA impact multiplier for each type of material to assess the environmental impact of a product based on its volume. To be precise, Aluminum = 1.29E-06 kg-$CO_{2\text{-}equiv}$/mm, Gray Cast Iron = 3.19E-07 kg-$CO_{2\text{-}equiv}$/mm, and Plain Carbon Steel = 6.29E-06 kg-$CO_{2\text{-}equiv}$/mm. In contrast to the proposed method, there are several factors that comprise the environmental impact of the machining process, which are primarily the machining time and the amount of material removed.

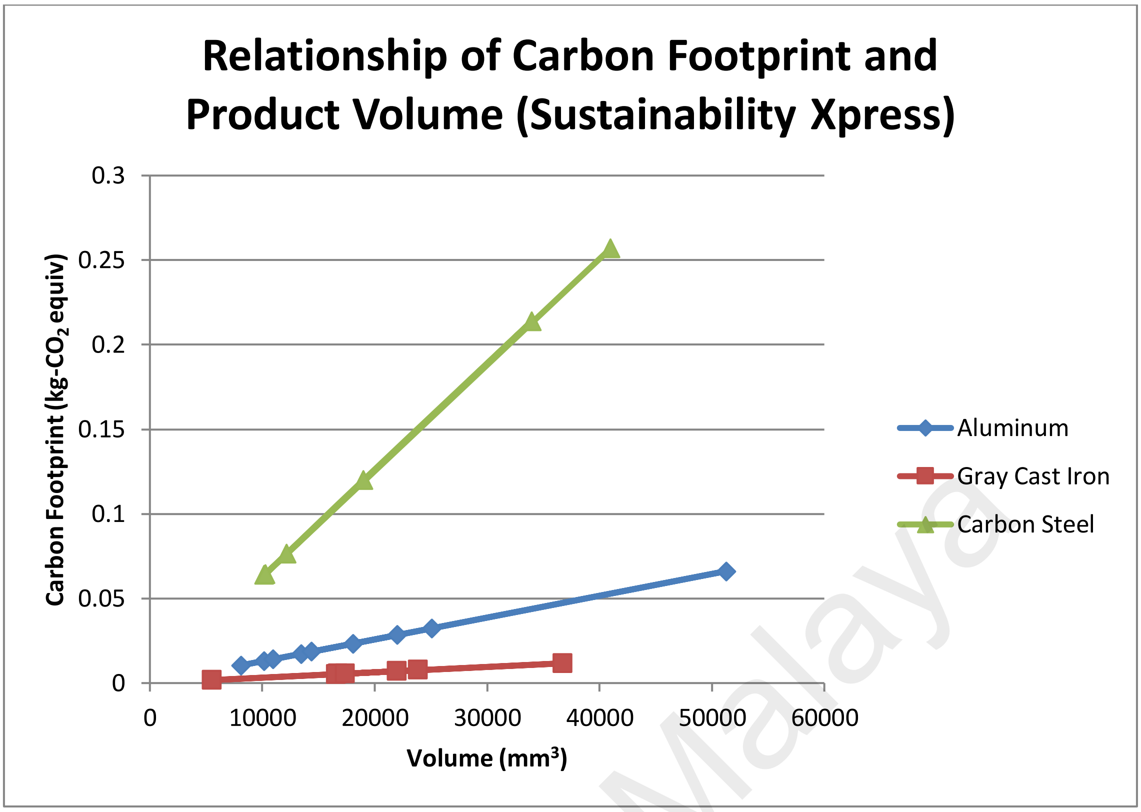


Figure 6.6 Sustainability Xpress' relationship between Carbon Footprint and Product Volume

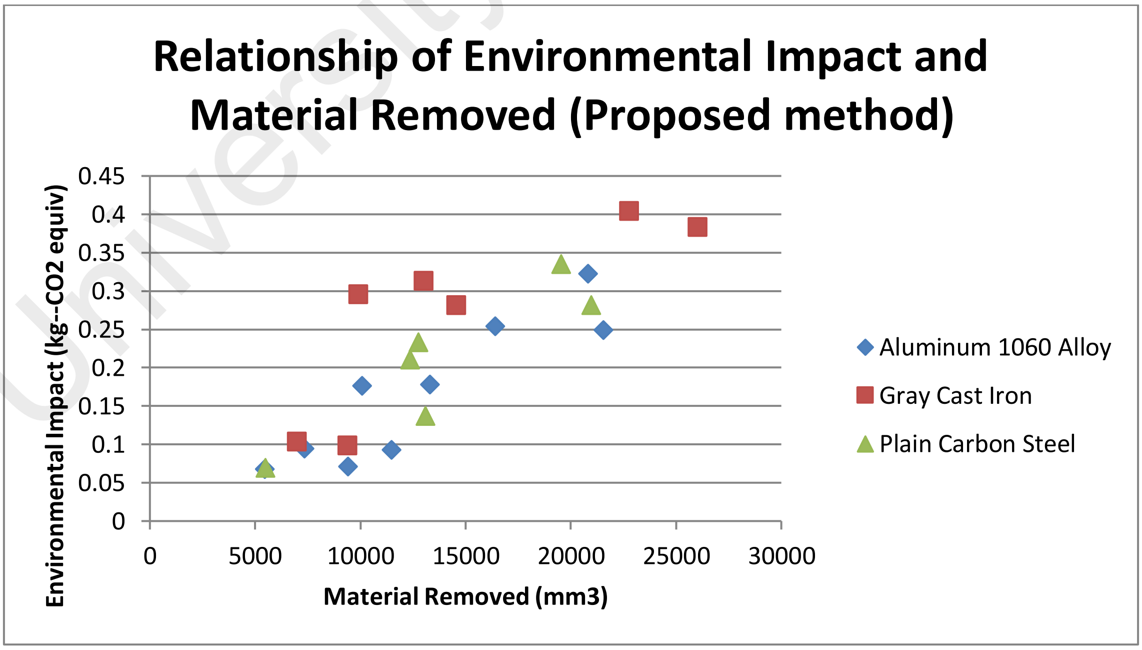


Figure 6.7 Relationship of Environmental Impact and Volume of material removed using the Proposed Method

Figure 6.7 shows the relationship of the environmental impact and the amount of material removed using the proposed method with a 70% correlation value. With the difference in design factors considered for the assessment of the environmental impact between the two methods, it is difficult to compare them. However, this also opens the door to criticize the methodology used by the Sustainability Xpress. The concept of using an LCA multiplier with the design of the product basing primarily on its volume may work on additive manufacturing processes like Injection molding, casting, 3D printing. However, subtractive manufacturing processes like Milling, drilling, Turning, EDM, which consumes power during the process of material removal from its stock, requires evaluations based on the material removal process per se, be it amount of material removed, amount of time to remove material, etc. If a product has more volume, it doesn't necessarily mean that it underwent longer machining, which is most of the time, the other way around. An improvement to this can be done by including information about the stock material. This way, the volume of the product can be deducted from the volume of the stock material and thus easily determine the amount of material removed.

Validating the environmental impact assessment method of the proposed method proves difficult as there are still discrepancies among the different assessment methods used in the industry. Comparisons are not easy because assumptions like forms and types of energy used vary and are sometimes not transparent to the LCA database user. Comparing the two methods, the Solidworks Sustainability Xpress uses LCA data of the Milling process on its entirety while the proposed method uses LCA data individually from its components (motors, electrical components, etc.).

6.5 Chapter Summary

The proposed method is validated on three individual aspects which are the key components of the system, namely: power consumption, optimization method and impact assessment method. The power consumption was validated by comparing the forecasted values with the actual machining of different design scenarios/ optimization method by product designers. It is important to use the power profile of machines to be assessed, instead of standard machine profile from literature. Usually, power profiles are given together in the machine's specifications, which are expressed in terms of Power (peak RMS).

The best designs for each criterion derived from the Taguchi method were also replicated by the proposed method using GA and even better solutions were found. Thus, the proposed method can compete with existing methods used in the industry in terms of power consumption assessment and optimization. In comparison with other CAD integrated environmental impact assessment tools, the proposed method could not be validated due to the differences in assumptions and factors considered. The Sustainability Xpress tool contradicts the theoretical projections of assessing environmental impacts of subtractive manufacturing operations, which includes milling.

CHAPTER 7

CONCLUSION

This chapter presents the conclusions of this study. It shows how the research aim and objectives have been met and the corresponding problems encountered during the research process. The contribution to knowledge and the research's significance to relevant industrial practitioners made by this study are shown, and in light of this, areas for future research are identified.

7.1 Review of the Aim and Objectives

In chapter 1, the aim and objectives of the research were detailed.

Research Aim

The aim of this research is to develop a methodology that will aid designers to reduce potential environmental impact of machining process in their designs.

Research Objectives

1. To critically review the related literature on current eco-design methods
2. To develop an integrated feature-based design method to assess the environmental impact of a product design, specifically on the impact of the machining process, to aid product designers.
3. To demonstrate the methodology through a case study by optimizing the design of a product according to its features with the minimization of potential environmental impact as its target objective

Both the aim of the research has been met through the accomplishment of the research objectives. The first objective is achieved by understanding the underlying principles of eco-design methods and the challenges and limitations of the state of the art. This helped in identifying what is still missing in the industry, or what needs to be improved in research. This paved way to the establishment of the second objective. Through this objective, the following conclusions can be drawn:

1. Implementation of environmental policies and regulatory controls still play a big role in the motivation to initiate eco-design in industries. However, there is a demand to identify the environmental impact of products and their plan of reduction through the Copenhagen Accord.

2. The consideration of environmental impact in early design stages lead to higher design cost savings. Therefore, a paradigm shift is needed so as not to perceive that the consideration of environmental impact is an additional task for the designer, but rather a vital step in design improvement.

3. Eco-design tools available cater to different stages of product design from its concept through its implementation. However, there is a demand for infrastructure to support eco-design activities, specifically in the aid of decision-making due to the fact that designers are not environmental experts.

4. State of the art eco-design methods provide suggestions on design improvement. However, they still lack the ability to provide concrete and/or quantitative solutions to design. Moreover, a direct feedback of these suggestions to the design.

The second objective focuses on the development of the methodology in the assessment of product design, specifically in its manufacturing stage of its life cycle. This was achieved through the integration of two systems namely the assessment and optimization.

The assessment of the environmental impact of manufacturing process considered the machining parameters of the milling process and Genetic Algorithm is used in the design optimization. The two systems were conveniently packaged as an excel macro program, where in turn could be connected to CAD/CAM systems. Current CAD/CAM systems allow the access of Excel data to be transferred to CAD drawings which serves as a feedback. The accomplishment of this objective drew the following conclusions:

1. A methodology to assess the potential environmental impact of a design based on its machining processes is developed through the integration of CAD/CAM and Excel systems.

2. Additionally, a feedback mechanism through the development of a multi-objective optimization system for product design is also integrated to the devised methodology to close the research gap pertaining to the lack of concrete and/or quantitative solutions.

3. The machining parameters considered to assess the environmental impact of machining are based on how design influences the manufacturing process.

4. A paradigm shift is imperative to shatter the misconception that reduction of environmental impact is expensive. A multi-objective approach to product design could obtain a compromise, or in cases an optimal design that satisfies all design requirements.

5. The GA optimization method represents the product design parameters as genes to be optimized and at the same time allows the satisfaction of multi-objective criteria.

The last objective focuses on the demonstration of the proposed method through a case study. This was evident in Chapter 5, where the case study was presented. The accomplishment of this objective draws the following conclusions:

1. The novel combination of Feature-based design and Life Cycle Inventory to assess the environmental impact of a specific design provides a detailed evaluation of the product based on the amount of resources consumed and waste produced.

2. The semi-automated design method is suitable to be incorporated to current design methodologies because it does not require the designer to have in-depth knowledge of environmental impact assessment and optimization methods.

3. The results in the validation on Chapter 6 show the discrepancies of the predicted energy consumption based on a different machine profile compared to the actual energy consumption during machining. It is therefore important to take into consideration the machine's own power profile.

7.2 Limitations of the Research

While a number of limitations are known to the author, it is not within the scope and objectives of the thesis to address these. Instead, the limitations serve to identify areas for improvement or future research subsequently addressed here.

The values of the environmental impacts are based on established LCI databases, which make the proposed system heavily dependent on published data. Available databases also collect information from various sources, which may not have standardized procedures in data collection.

The accuracy of the computation of environmental impact by the proposed system could not be validated because the existing methods are also not established as accepted methods and their discrepancies. However, the proposed method can be used to monitor design improvements in comparing different design scenarios and choosing the best designs among them.

The proposed method still requires the designer to identify design parameters that needs to be optimized. The nature of the method is semi-automatic and does not fully replace the job of a designer.

The functional objectives of the design is always dependent on the designer and his/her expertise is still needed in the development of an optimization model, as these needs to be defined first and fore most.

The study did not focus on the effect of the changing GA parameters in optimization.

7.2.1 Problems and Difficulties encountered

The research has some problems encountered which workarounds were made to overcome them. Choosing the validation method to prove the viability of the proposed method prove to be a daunting task as there are no established methods to compare the proposed method in its entirety. Thus, the validation is divided into 3 different methods, to validate each module instead.

As a result of the validation, it was found out that a power profile specific to the machine being studied is required. The task does not present physical difficulties, but the additional task required additional time to conduct experiments.

7.3 Contribution to Knowledge

The academic contribution of this study is to answer the research gaps identified in chapter 2.7.1.

To answer the research gap #1, from chapter 2.7.1, current Eco-design solutions provide suggestions on how a product can be improved, but still lack the concrete solutions that are needed. The novel use of GA to optimize design parameters is able to address this gap. The resulting design solutions are quantitative and include the type of feature and their dimensions in the design of the product. Using GA allows designers to have multiple design options to choose from, which are already optimized to satisfy the criteria. The research is also able to address the applicability of GA in sustainable product design.

To answer the research gap #2, from chapter 2.7.1, current green manufacturing technologies involves the life cycle assessment of the manufacturing processes to compute the environmental impact. This leads to the improvement solutions at the end of the pipeline. An early assessment of the potential impact in the manufacturing process during the design stage can further reduce both cost and potential environmental impact through direct feedback of possible design parameter improvements to the designer. Due to the integrated nature of the proposed method, the optimum product design parameters can be easily translated into a CAD model through the use of Design tables. This provides a quick response to the design process and immediately validates them.

To answer the research gap #3, from chapter 2.7.1, it is suggested to use machining parameters as factors for environmental impact: Integrated systems solutions provide high environmental improvements. However, current CAD+LCA integrated solutions fail to consider the machining parameters as factors in sustainable product design. Using feature-based design (FBD) is the novel solution to accommodate the machining parameters. This also allows the method to be flexible and modular, in a sense that if additional features are needed to be added to the design, it can easily be added and the impact easily assessed.

7.4 Contribution to Practitioner

Product designers are responsible to translate requirements into design specifications and concepts. Many aspects of the product requirements are according to the customer and sometimes there are little or no considerations of the product's environmental impact. Though there are existing design softwares that have developed an environmental impact assessment as an "add on" to their software systems, they have limited or inaccurate representation of the environmental impact particularly on the manufacturing processes of the life cycle assessment. They focus mainly on the material aspect of the design.

The proposed system can aid designers in providing design solutions that satisfies the customer's requirements and at the same time add value to their work through the suggestion of eco-friendly alternatives. Since the focus of this research is in the impact of design on manufacturing processes, the system developed may complement the existing "add-ons" of design softwares.

The proposed system also eliminates the need for designers to undergo additional training for life cycle assessment just to gain knowledge on environmental impacts of different manufacturing processes and types of materials to be used.

7.5 Recommendations for future research

The beauty of this research is its modular nature. This means that additional functions can be added in terms of assessment of the product. In cases where the manufacturing processes have additional factors that could contribute to the energy consumption or waste, for example in dry milling, where compressed dry air is used instead of water-soluble coolant, a new power profile for the inclusion of air compressors could easily be added. Its modularity also means that additional manufacturing processes could be assessed simultaneously, providing a more complete assessment. This can lead to the research of different environmental impact factors of different manufacturing processes, and furthermore of different product life cycle stages (raw material extraction, use, disposal, etc.).

In another aspect, the parameters for environmental impact can be expounded and with the addition of the societal and health factors with cost, the assessment supports the sustainability concepts, which can evolve to design for sustainability. Research for the effects of the manufacturing processes on the health of the machining operators could broaden this area.

Lastly in the field of system integration, a small research can be suggested for integration of the proposed system with a CAM software, where the machining time, spindle speed and feed rate are automatically computed. Though the formulas used in this research are all based on theory, there are more sophisticated models commercially available. This will also be very practical for the quick simulation of the machining processes.

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