Accelerating Cleantech Hardware Product Development

by

Erin Elizabeth Looney

Submitted to the Department of Mechanical Engineering
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Abstract

Startups in the Cleantech sector have historically had poor return on investment and high failure rates when compared with the medical or software sectors. One reason given for the disappointing outcomes of many Cleantech companies is slow product development (PD) and cycles of learning. In this thesis, I explore the major bottlenecks in hardware product development (PD) including slow cycles of learning, especially in Cleantech. I then develop technical and operational interventions to help overcome these obstacles. I accomplish this through 55 interviews with hardware startup chief executive and chief technology officers worldwide and subsequent analysis of the data from these conversations. By analyzing this data, I find ways to accelerate the innovation process and work toward applying these to Cleantech hardware product development.

First, I find that prototyping is the largest time sink for hardware startups with a median of 2.5 years. I further find that prototyping times are not correlated with certain product complexity metrics. This suggests that something other than technological constraints determines prototyping times. To examine this further, I investigate the impact of innovation models on prototyping times. I find that a flexible, natural innovation model can accelerate early-stage innovation while a structured PD approach is preferred for later-stage innovation.

Then through qualitative coding of the interview transcripts, I find another PD bottleneck in relationships with the key stakeholders of investors, customers, and manufacturers. I find several best practices regarding these relationships, and I propose that codifying some of these as requirements in the traditional sense might be a promising strategy to accelerate PD timelines. Next, I present an outlook for technological acceleration strategies that are cutting edge and have only just begun to be used by startups. These include computational tools like automation, machine learning (ML), and high performance computing (HPC), as well as physical tools like 3D printing.

Lastly, I present a computational tool for testing solar photovoltaics as an example of a PD acceleration method. This tool, called Representative Identification of Spectra and the Environment (RISE) uses K-means, a machine learning clustering algorithm. The RISE method overcomes the shortcomings of past spectral classifiers used in industry and academia. This method is technology agnostic and the two parameters of RISE, k_1 and k_2 can uniquely classify all spectra worldwide unlike the commonly used APE classifier. I further demonstrate the RISE method in practice using LED-based solar simulators to test solar devices, capturing more performance data relevant to real world conditions per unit time than current standard testing allows. Using only 18 representative spectra, I correctly reproduce energy yield differences between silicon solar cells and CdTe solar cells with an accuracy of less then $1.5 \pm 0.5\%$ as compared to over 5% when using STC. With the findings enumerated above, this thesis adds data-driven technical and operational strategies to the Cleantech community's playbook to accelerate cycles of learning.

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Chapter 1

Introduction

The topic of this thesis is accelerating the development and commercialization of new "clean" technologies, many of which are not succeeding as products. As climate change is a time-sensitive issue, the inability to commercialize new technologies is an issue the world cannot ignore. Furthermore, business-as-usual solutions are not good enough. Societies will need to discover, design, and develop new technologies, processes, and policies faster and more effectively than ever before to meet this challenge. In this thesis, I work to understand what is preventing startup companies trying to commercialize Cleantech from succeeding at rates similar to other market sectors such as medical and software. I devise new solutions and strategies designed to help Cleantech startups overcome these obstacles, and I give a specific example of one such strategy for the sector of photovoltaics. In this introductory chapter, I chronicle the rise of the Cleantech sector, what my approach to this research is in contrast to literature, and define the specific research questions I will address in this work.

1.1 Defining Cleantech

The term "Cleantech" first emerged in the late 1990s in venture capital (VC) circles and was popularized when the Cleantech Venture Network was created in 2002. This same organization, now called the Cleantech Group has a working definition of Cleantech[1]:

> "Cleantech is new technology and related business models offering competitive returns for investors and customers while providing solutions to global challenges. Cleantech spans many industry verticals and is defined by the following eleven segments: Energy Generation, Energy Storage, Energy Infrastructure, Energy Efficiency, Transportation, Water/Wastewater, Air/Environment, Materials, Manufacturing/Industrial, Agriculture, and Recycling/Waste." [1]

This definition does not precisely define the criteria that a new technology or business model must meet to be counted as Cleantech. In response, several financial market analysts and others have created more exact definitions. Dow Jones VentureOne says that Cleantech companies are:

> "... defined as companies that directly enable the efficient use of natural resources and reduce the ecological impact of production. The impact of Cleantech can be either to provide superior performance at lower costs or to limit the amount of resources needed while maintaining comparable productivity levels." [30]

Another definition from Thompson Reuters and National Venture Capital Association says:

[1]This definition was presented in a 2018 presentation by Richard Youngman the director of the European branch and vice president of global research at Cleantech group

> "Clean technology investment focuses on innovations which conserve energy and resources, protect the environment, or eliminate harmful waste." [30]

The National Resource Defense Council defines Cleantech companies differently:

> "They use new, innovative technology to create products and services that compete favorably on price and performance, while reducing mankind's impact on the environment." [20]

All four of these definitions give criteria for classification of cleantech companies vs non-cleantech companies with varying degrees of specificity. For example new technologies that "provide solutions to global challenges" could describe many non-cleantech companies, as could "providing superior performance at lower cost." It is these criteria in conjunction with the mandate to "conserve energy and resources, protect the environment, or eliminate harmful waste" that make it cleantech.

The difficulty in classifying Cleantech companies is further muddied by the desire of companies to be designated as "Cleantech" for marketing reasons. Being a Cleantech company is a profitable public image, and therefore many companies endeavor to be classified as such whether or not they meet the criteria laid out above. Furthermore, the exact ways in which a company must operate to qualify as "protecting the environment," for example, are not defined. While rigorous definitions and classifications are desired for clear company designation, for this thesis whether a company can be designated as Cleantech is not decided by the author but by the community. Self-regulation within the Cleantech community is taken as a proxy for rigorous classification. Companies that proclaim to be Cleantech and are accepted as such by the community are therefore designated as Cleantech in this thesis.

1.2 Cleantech 1.0: Silicon Valley takes on Climate Change

In the early 2000s, two world trends coincided to create a new economic sector. One was the increasing consensus on the existence of anthropogenic climate change and its devastating effects on the climate of our world [61]. The other was the rise of the Silicon Valley tech sector and venture capital (VC) successes that dominated the corporate world as part of the fifth technological revolution of Information Technology [137][44][115]. As the Dotcom Tech bubble began to collapse in 2001, VC's looked elsewhere to invest and the Cleantech sector emerged in the early 2000s as an investment opportunity[106]. Technologies that are now a part of Cleantech existed before 2000, but the VC hype brought attention to these technologies in a new way, spurring investment and further innovation. In the five years from 2006 to 2011, venture capitalists invested over 25 billion dollars in Cleantech 1.0 [18][48].

1.2.1 Outcome of Cleantech 1.0

The outcome of the Cleantech 1.0 was bleak for investors. More than half of the investment was lost, and Cleantech companies failed more and had lower rates of return than competing VC sectors such as medical and software which can be seen in Figure 1-1[48]. These poor outcomes have led to a major drop in investment in Cleantech startups.

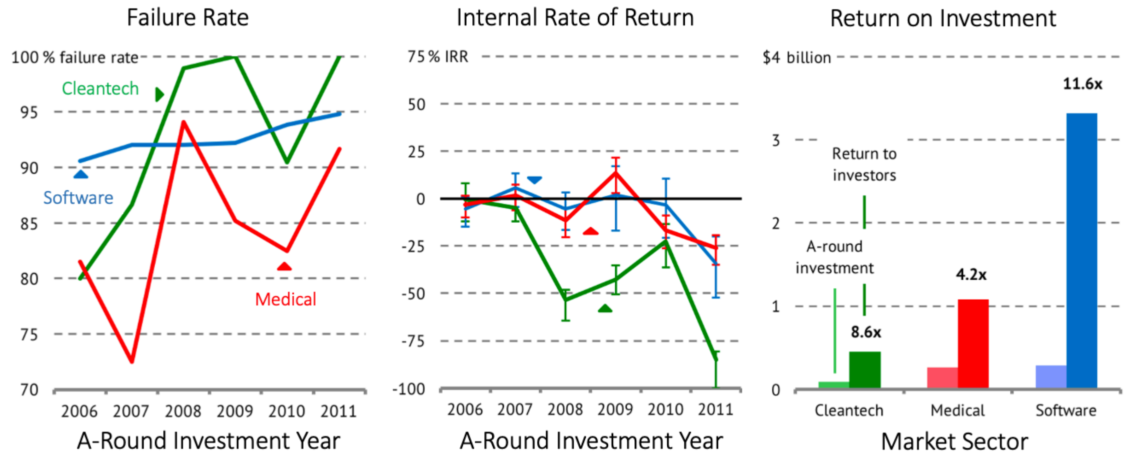


Figure 1-1: Cleantech vs. Other Sectors

Cleantech had high failure rates and negative rates of return as well as low return to investors of cleantech when compared to other sectors.[48]

There have been several responses by investors to try to overcome the demise of Cleantech 1.0. Each response comes with an assumption of why Cleantech 1.0 failed. Here are three of the main reasons given for the difficulties of Cleantech 1.0 which I document here along with the strategies some investors have taken to overcome them.

1. One assumption is that the technology risk was poorly understood by investors. According to a policy analyst a Bloomberg New Energy finance, "What a lot of them (in the VC community) didn't bargain for, and, frankly didn't really understand, is that it's almost never going to be five guys in a garage. You need a heck of a lot of money to prove that you can do your technology at scale." [36] This reasoning caused several investment groups to drop out of any investment in Cleantech all together. While others have hired technical experts to overcome the perceived knowledge gap.

2. Another reason given by the investment community for the disappointment of Cleantech 1.0 is the complex market space of energy. Many of the Cleantech companies invested in were renewable energy technologies with small margins to make profit trying to compete in the incumbent commodity market of energy with a tough regulatory environment. This reality meant that any new companies hoping to innovate in this space had to compete on a cents per kWh level with existing technologies. Also, the energy market notoriously fluctuates so if the prices of competing energy sources suddenly drop as happened in 2009 with natural gas in the United States, new companies and the technologies they deliver had little to no ability to withstand that market shift.[94]

3. Another assumption of why Cleantech 1.0 did poorly is that the cycles of learning or timeline to market for these technologies was too long for investors wanting returns. One Cleantech VC describes this problem saying that the average time from founding to IPO was 8.3 years, so "If you're signing up to build a clean-tech winner, reserve a decade of your life." [113] Some venture funds have developed a strategy in response with longer funds and blended capital to overcome this.

Startup companies have also developed strategies for overcoming some of these barriers. For example, many Cleantech companies now target niche beachhead markets first rather than the bigger more lucrative ones. Another popular strategy involves working closely with incubators and accelerators that hold institutional knowledge of markets and regulatory environments and have demonstrated successful product launches.

1.3 Thesis Motivation

To date, strategies by investors and companies to overcome the three problems outlined above have not been proven to be broadly effective, but there have been anecdotal successes. There is evidence that slow cycles of learning are worse for Cleantech startups than others. In Figure 1-3 it is shown that Cleantech has the longest exit time on average compared to medical and software companies.

Figure 1-3: Industrial Sectors Years to Exit

The differences in time to exit between three industrial sectors are shown. The cleantech distribution shows a longer time to exit than medical and software [19].

Software companies are the favorites of the VC community with 3-year average exit times when investors can start receiving return on investment (ROI). Medical, often slowed by medical regulations has longer exit times than software, but these are well understood and can be alleviated through investment by wealthy pharmaceutical or medical device companies. Cleantech has a bi-modal distribution with 4-year and 8-year peaks, and unlike the pharmaceuticals or devices in the medical sector, there is not a specific government mandated path to market. There are also few if any large Cleantech companies with high margins to keep startups afloat until they are ready to exit. These realities demonstrate the need to accelerate cycles of learning and time to market for Cleantech startups to attract investment capital and work toward the larger goal of a sustainable future.

With this thesis, I focus on one of the major reason given for Cleantech 1.0's disappointing outcome: slow cycles of learning and long times to market. I hope to add data-driven technical and operational strategies to the Cleantech community's playbook targeted to accelerate product development(PD).

1.4 Cleantech in the literature

Several research communities have worked toward understanding and helping the Cleantech sector succeed including business schools, sociologists, economists, geographers, Cleantech policy groups, etc. There is a focus within some of these research communities on writing case studies to understand specific successes or failures within cleantech companies. Many lessons can be learned from case studies including how individual companies overcame or failed to overcome the major setbacks common to Cleantech. There have also been articles published on the Cleantech industry as a whole, including Cleantech clustering, financial, and policy strategies to boost the sector. In Appendix A, I give an overview of this literature. The majority of Cleantech literature discusses how to overcome barriers to commercialization with industrial clustering, financial, and policy strategies. This research has focused on addressing obstacles cleantech companies face from a "top-down" perspective. By "top-down" I mean through research implemented outside of the engineering discipline focusing on strategies for implementation by governments and large institutions.

1.4.1 My approach

In contrast to the majority of literature, I approach this research from a "bottom-up" perspective. A bottom-up approach in this case indicates two things:

1. I gather data as an engineering practitioner by talking directly to the people

currently working to commercialize Cleantech from within startups rather than from secondary sources.

2. I formulate technical and operational strategies and solutions that can be implemented by the startups on the ground rather than strategies for funding and policy groups.

This point of view can shed new light on the obstacles faced by Cleantech 1.0 and how to overcome them.

1.5 Research Questions

Through an examination of 55 hardware startup companies, of which around half are designated as Cleantech, I seek to understand the pain points and bottlenecks within the product development process. Focusing on slow cycles of learning and long exit times for these companies, I formulate several research questions to explore. The specific research questions I hope to answer are enumerated below.

Main research questions:

1. What are the main bottlenecks in hardware product development, especially in Cleantech?

2. Are there technical or operational interventions that can speed up cycles of learning for hardware startups?

3. How might new state of the art computational and hardware tools be used to accelerate hardware product development?

Through quantitative and qualitative analysis of the interview transcripts, along with cleantech product design experience, placed within the available literature, I formulate strategies and tools for accelerating product development in Cleantech.

1.6 Thesis Outline

A short outline of the thesis is as follows.

In Chapter 1, I present the background of Cleantech 1.0 and describe the gaps missing in literature that this thesis helps to fill.

In Chapter 2, I cover the interview study, including sample selection, transcription, analysis methods, and how hypotheses were formed and tested.

In Chapter 3, I explore research outcomes from the interview study finding and analyzing pain points including prototyping, product complexity and innovation models.

In Chapter 4, I explore how relational requirements affected the product development process for the interviewees, including those with customers, investors, and manufacturers

In Chapter 5, I examine technical strategies used by the interviewees, and I explore cutting edge tools for future use in prototyping, specifically the design, build and test steps of product development.

In Chapter 6, I present a spectral classification method called Representative Identification of Spectra and the Environment (RISE) as an example of an acceleration tool for solar photovoltaics testing.

In Chapter 7, I use the RISE method experimentally to demonstrate its potential use in accelerated testing for energy yield predictions for different climate zones in laboratory or industrial setting.

In Chapter 8, I summarize and conclude the thesis, reiterating my main contributions to the literature.

Chapter 2

Accelerating Cleantech Interview

2.1 Introduction

The struggle of early stage Cleantech companies to succeed was outlined in Chapter 1 with examples of the research done to understand these barriers. One of the reasons for the failures of these companies is the slow cycles of learning inherent in their hardware development.[?] Much of the literature about Cleantech to date offers analysis and strategies from a top-down approach including financial and policy strategies and theory that could help the Cleantech sector succeed. See Appendix A for more detail. In contrast, this study takes a bottom-up approach developed by talking directly with the technologists that make up the Cleantech companies and determining technical and operational strategies to be implemented directly by them. Specifically a set of questions was developed in order to:

1. Map and analyze company product development (PD) timelines.

2. Determine pain points and slowdowns in PD.

3. Discover and outline solutions to accelerate PD.

These interview goals are almost exactly the same as the research questions from Chapter 1, with the addition of mapping PD timelines as a strategy to inform items 2 and 3. In this chapter, I introduce the interview methods and sample selection, as well as explain each section of the interview.

2.2 Interview Methods

I chose a facilitated survey format for this interview combining my engineering domain expertise with sociology research methods both quantitative and qualitative. The purpose of the study is to map workflows and understand pain points along the PD process which requires the interview to be of a certain length and depth, containing approximately 170 questions and lasting between 45 minutes and 2 hours. The interview questions are enumerated in Appendix **??**. Also, enough companies must be interviewed to get a broad picture of the PD path for hardware startup to find generalizable conclusions. To accomplish this breadth, I completed 55 interviews with N between 30 and 55 for individual questions depending on the company. Therefore, my choice of approximately 50 interviews lasting about one hour was targeted for a mix of breadth and depth allowing for a broader understanding than what typical case studies allow as well as a deeper analysis than the scope of typical surveys. This unique study provides a new "bottom-up", interdisciplinary, and mixed-methods perspective into the hardware PD process specific to Cleantech.

The content of the interview is outlined by the *Product Design and Development* textbook by Ulrich, Eppinger, and Yang[153], used in the MIT product engineering class 2.009 to guide student through the PD process as it might happen within

Table 2.1: Interview Contents from PD Process

Section 1	Personal and Company Info
Section 2	Product Planning
Section 3	Requirements
Section 4	Modeling
Section 5	Concept Generation and Selection
Section 6	Complexity
Section 7	Prototyping
Section 8	Manufacturing
Section 9	Overview

a company setting. The generic PD process was adapted from this text for the interview as can be seen below in Table 2.1.

2.2.1 Sample selection

The makeup of the sample for the interview study determines what conclusions I can draw from the work. My goal in picking the subjects is therefore to find a sample that best represents the larger population of companies generally. For this work, a purposeful sampling technique was used meaning that the sample was selected based on characteristics of the population and study objectives stated above [117]. The study encompasses early stage hardware startups in general with a focus on the subset of participating Cleantech companies. With several market segments involved, the data can be compared between sectors including Cleantech, Medical, Consumer electronics, IoT, and others.

Participants were contacted through online forms, LinkedIn connections, and publicly available email addresses. Of the over 500 cold contacts made, around 40 agreed to the interview, an acceptance rate of less than 10%. The companies chosen for an interview were therefore based on willingness to participate, making it a non-probability sampling technique. This brings some amount of bias to the companies interviewed as they self-selected to be interviewed. However, there were some factors combating this, as there was a countervailing snowball sampling effect. For example, one company CEO would introduce me in person or by email to other company leaders that would fit into the study. The likelihood of these subjects participating was much higher than if I had contacted them cold.

At first, to start finding subjects, I targeted hardware accelerators as potential interview sites where many interviews could be accomplished. I contacted over 20 hardware accelerators to set up pathways for interviewing participating companies. Unfortunately, the accelerator leadership would not allow mass contact of their portfolio companies. Therefore, I determined all contacting would have to be done by cold-contacting individual companies.

In the end, 55 companies from around the world agreed to participate. The companies can be seen in Figure 2-1.

Figure 2-1: Global Map of Interviewed Companies

Locations of the companies that participated in the study. A majority are in Boston and Singapore with others scattered around North America and Europe.

2.2.2 Workflow Mapping

One major component of the interview is workflow mapping where I established a timeline for each company's PD process to understand how long the individual PD steps take. I first ask interviewees for an incorporation date; all following timeline questions are asked with respect to the given incorporation date (i.e., How many months before or after incorporation was X step started or finished?) An example of a timeline from the study with the major PD milestones and tasks can be seen in 2-3.

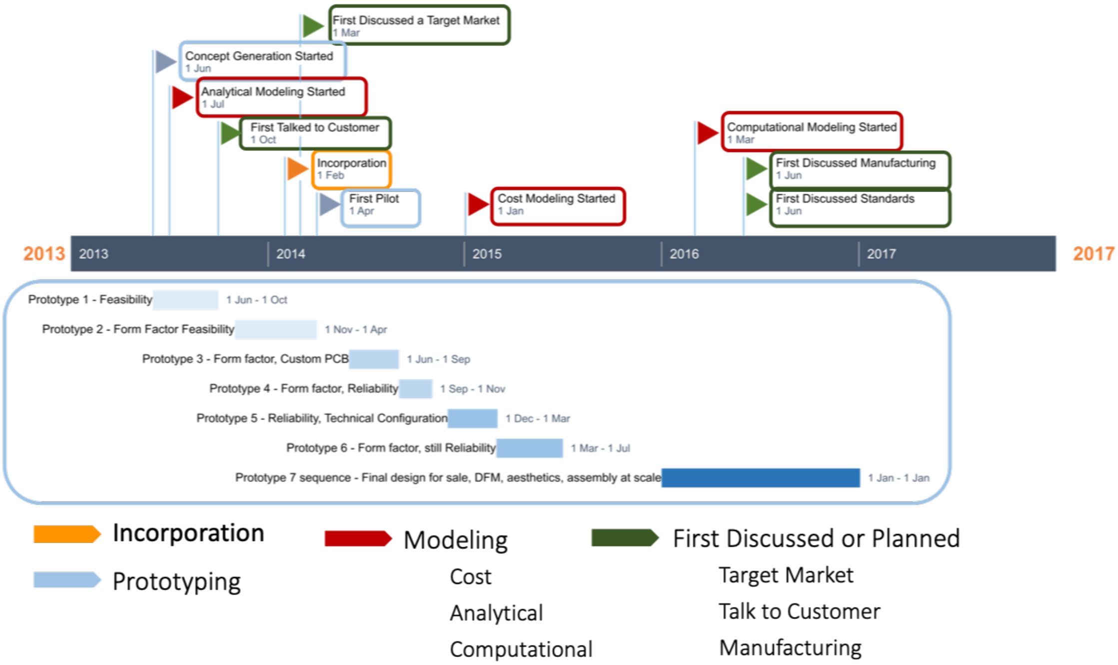


Figure 2-3: Example Workflow Timeline

An example of a workflow timeline developed through interviews. Incorporation (orange), prototyping (blue), modeling (red), and operational milestones (green) are key components.

2.3 Interview Sections

In this section I explain the details of both the content and design of each interview section.

2.3.1 Personal and Company Info

The goal of the first section of the interview is to understand who the interviewee is and the basic history of the company they are a part of. First, I focus on the interviewee's characteristics including academic degrees and position in the company as seen from the results in Figure 2-5. The majority of participants have a background in engineering or science and are either the CEO, CTO and/or founder of their company. In addition, the majority of the participants have advanced educational degrees beyond a bachelor's degree.

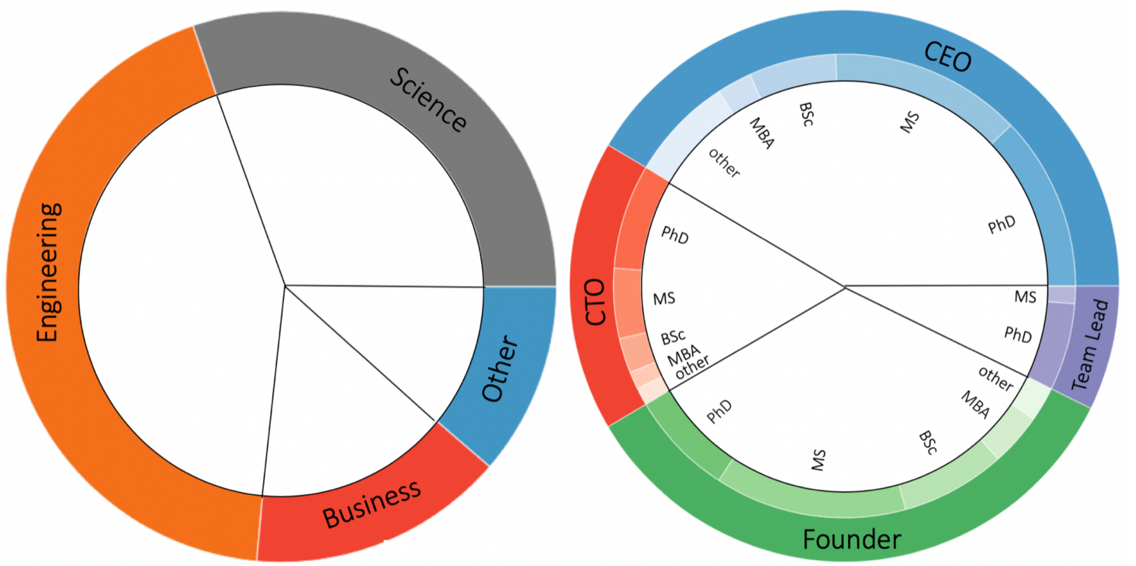


Figure 2-5: Aggregated Interviewee Information

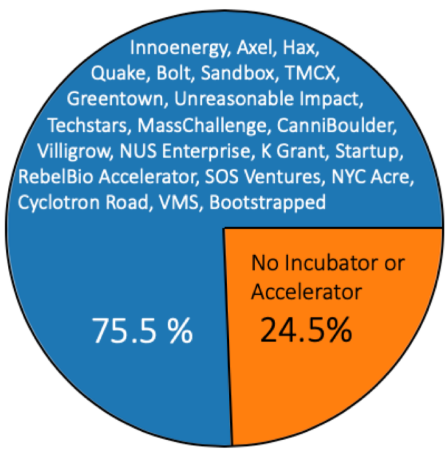
Breakdown of the survey participants in terms of position in the company and highest academic degree.

After understanding who the participants are, I ask about company information:

- How many employees do you have?
- Are you a business-to-business (B2B) or business-to-customer (B2C) company?
- What type of funding sources do you have or have you had?
- How do you procure funding?
- What is your company's estimated net worth?

- Was significant technology or business development done within a research institution or another company?
- Are you or have you been a member of incubator and accelerator?

All of these questions are designed to develop an understanding of the sample set and what conclusions can be taken from the interviews. Some of these results are shown below in Figure 2-7, Figure 2-9, and Figure 2-11, and some will be analyzed in future chapters.



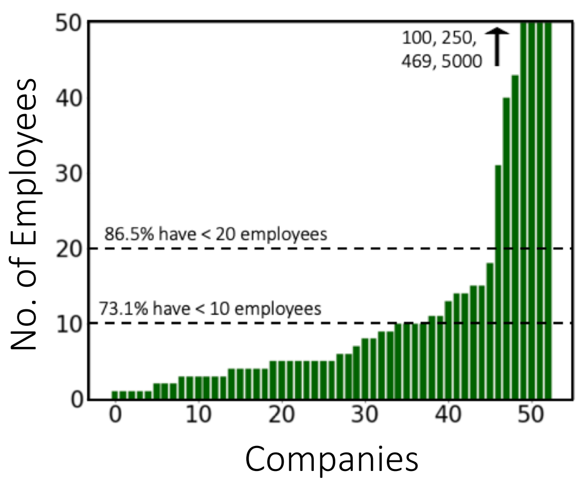


Figure 2-7: Aggregated Company Information I

Left: How many companies were or had been a part of an incubator or accelerator program during their PD. Right: Number of workers the sample companies employed.

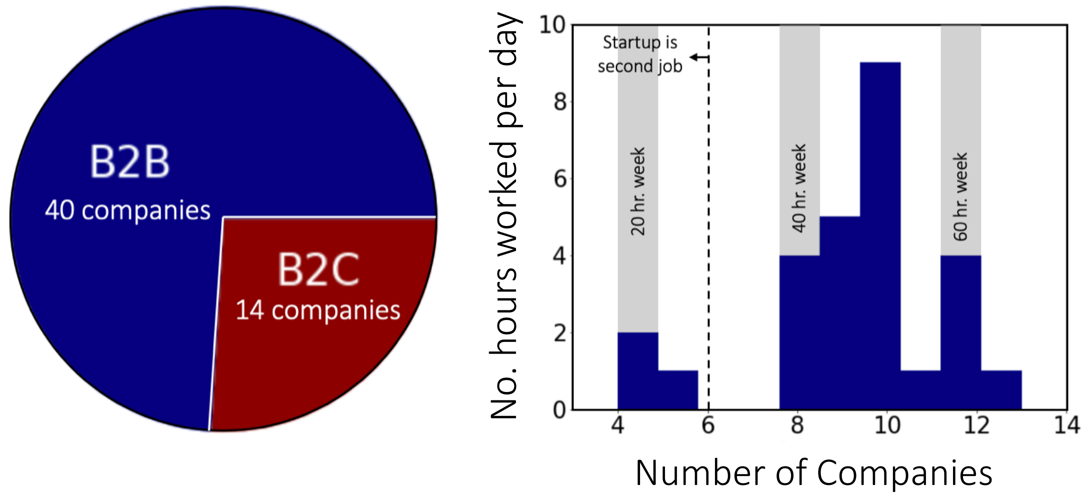


Figure 2-9: Aggregated Company Information II

Left: Number of business-to-business (B2B) vs. business-to-customer (B2C) company types in sample. Right: number of hours worked by average employee in company per day.

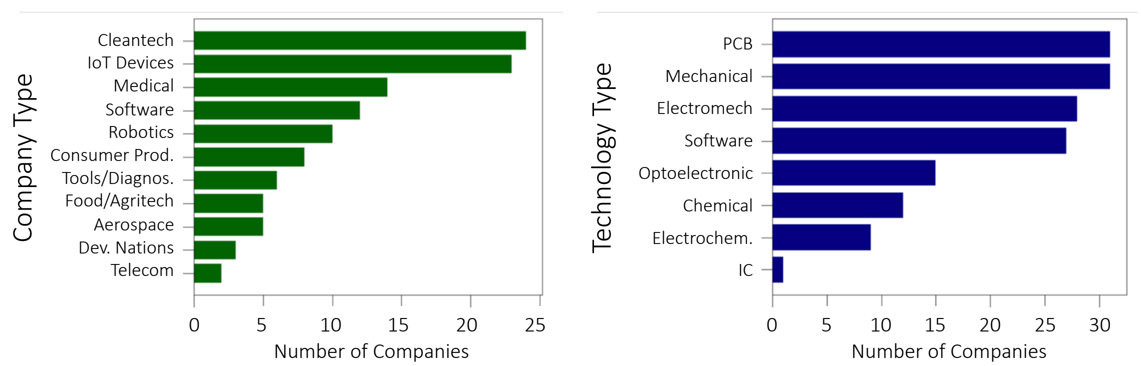


Figure 2-11: Aggregated Company Information III

Left: Company type of which many companies picked more than one category. Right: Technology of which many companies picked more than one category.

2.3.2 Product Planning

The product planning section is the first PD step adapted from the generic PD process flows from the textbook [153]. Product planning is the part of PD where a basic schedule of the process is laid out and strategic milestones are envisioned by the team. I ask questions in this section to tease out how the company planned for PD, probing the startup's strategic vision for their specific PD. I begin with questions taken from the textbook to see if the companies participated in these basic strategy development steps:

- What kind of product development is undertaken?
- What is the competitive strategy?

Answers to these questions can be seen below in Figure 2-13.

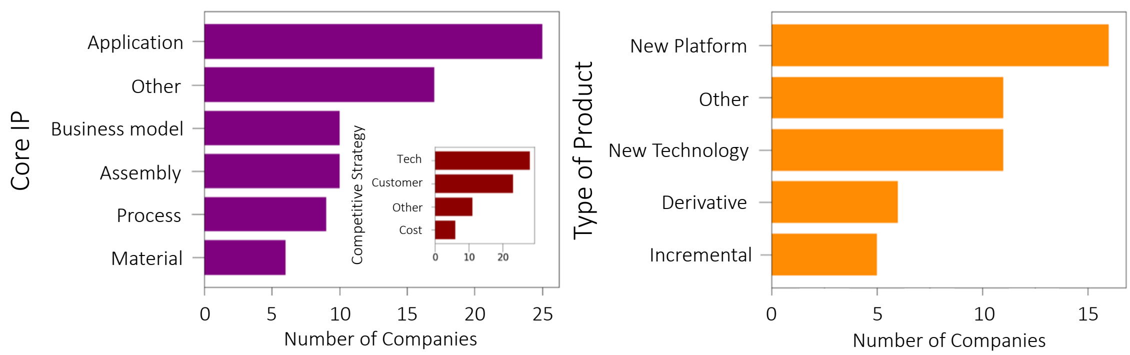


Figure 2-13: Aggregated Product Planning Interview Responses

Left: The core IP type and competitive strategy of the companies. Right: The type of product development being undertaken by the company.

I find the majority of companies have core IP in novel applications, and the type of product development being undertaken is most often a new product platform or new technology.

The purpose of the next part of this section is how and when the company targets a market. This is a key step in product planning and also the initial interview inquiry relating to the "first milestones" as identified in the workflow mapping. First milestones are defined as the first time the employees of the startup seriously planned for important PD steps, in this case targeting a market. These milestones are an indication of how aware the startups were of the obstacles ahead for them as a hardware startup. Other "Firsts" include milestones such as first talking to a customer, designing for manufacturing, and designing for standards and certification.

- When did you first target a market with respect to incorporation?
- What was the hardest part of targeting market?
- Were any specific tools or methodologies used?

I will go through analysis of these answers and the rest of the interview in future chapters.

2.3.3 Requirements

The next section is designed to learn how the company deals with finding and documenting product requirements. Engineering requirements, as defined by the *Fundamentals of Systems Engineering* class at MIT, "describe the necessary functions and features of the system one is to conceive, design, implement and operate."[29] This is a narrow definition of requirements focusing on technical elements which is broadened and discussed further in Chapter 4.

In the requirements section I first ask if the company perceives their design as user-centered:

- Would you characterize your product as "user-centered" design? Please answer: Yes, Somewhat, Neutral, Not Really, No

This question is asked to understand if the company identifies as using the design principles now taught in some engineering schools and design workshops called user-centered design (UCD). The background of UCD and its importance to PD for hardware companies is expanded on in Chapter 4.

Next, I seek to understand why and how companies gathered customer preferences and determined requirements from these preferences and other engineering constraints. I asked the following questions:

- Did you talk with customers before starting design?
- How many business days before or after the incorporation date did you first speak with them?
- How did you gather customer preferences?
- Were traditional engineering requirements identified and targeted for design? [Yes, Less officially worded, No requirements discussed]
- What types of requirements were included? [Functional, Performance, Interface, Maintainability, Reliability, Others]
- If you didn't use traditional requirements, how were the user's needs quantifiably turned into design concepts?

2.3.4 Modeling

The next section in the interview is about modeling. I cover the technical modeling of the product, including analytical and computational modeling, as well as business modeling, including cost modeling. Analytical modeling is defined as a "mathematical model with closed form solution." To prompt thinking about analytical modeling, I refer to this as the "back of the envelope," "proof of concept" equations that give approximate ideas of the constraints and requirements of the system being designed. Computational modeling is defined as a computer-based simulation used to analyze the complex physics of the system. Lastly, cost modeling encompasses a broad range of activities revolving around the prediction of capital costs and cost of manufacturing of a product versus projected retail value.

An entire section is devoted to this due to the variety of approaches a company can take toward modeling, from not bothering to do it at all to modeling extensively. Either of these extremes could change the pace of PD for better or worse. One difficulty with actually mapping modeling timelines is the non-contiguous nature of many of these models. Often they are started and put down many times as the company develops, evolving as needed. As a result, most of the modeling milestones placed on the timelines are when the modeling was first started or finished.

For each type of modeling I asked:

- Did you do (analytical/computational/cost) modeling?
- How many days after incorporation was it started?
- How many business days until first usable results were produced?
- How many people worked on it?
- How much do you think technical modeling negatively affected the timeline? [None at all, A little, A moderate amount, A lot, A great deal]

2.3.5 Concept Generation and Selection

Concept generation (or ideation) and selection are important creative steps in the PD process that are often done uniquely based on the makeup of the company. I asked the interviewee to think of when they were first brainstorming and developing the idea for the product, and explain how this process looked for then. During their narrative I would ask the following questions to learn specifics.

- When was the first ideation round started with respect to incorporation?
- How many people were generally a part of ideation?
- How long did a round of ideation generally last?
- How many concepts were created in an ideation round?
- How long was more than one concept pursued?
- Do you think designs were killed off too quickly?
- Do you think designs were pursued too long?
- How was a concept selected? [External decision, Product champion, Intuition, Voting, Web-based survey, Pros and cons, Prototype and test, Decision matrices, Other]
- How many people were generally a part of concept selection?

2.3.6 Product Complexity

The next section of the interview was about the product itself, not just the process. This was added so that different types of products could be compared via several complexity parameters. These complexity parameters are adapted from a literature review of complexity metrics for products. Within engineering, there is no standardized definition of complexity[92], and product complexity has been quantified in dozens of ways depending on the study purpose and available data set. Most academic fields and sub-fields have a different definition and metric for complexity. A desired metric for this work is one that is quantitative and can be plotted against time to prototype. Here I review the relevant literature used to create the complexity interview questions and metrics I adapted to create a complexity metric for this study.

Product Complexity in Literature

In this section, I will discuss how I adapted questions for the interview from the existing literature. First, Novak and Eppinger defined product complexity as having three major components: (1) number of components to specify and produce, (2) extent of interactions to manage between these components, (3) degree of product novelty [114]. Because the specific questions they asked in their study pertain only to vehicle systems, this cannot be used directly for this work, but the major three components are applicable. The base of the complexity questions for this interview come from these three major components.

That same year, Tang and Salminen compiled a list of works on complexity from literature including different strategies for addressing complexity, new complexity metrics, and a wide range of research fields and applications. Out of all of the literature reviewed, only two contain quantitative complexity metrics for hardware [145]. First, axiomatic design is defined by Suh et al. as time-dependent (combinatorial and periodic) vs. time independent (real and imaginary) complexity. Each of these is a measure of uncertainty in achieving specified functional requirements [144]. To formulate this metric, probabilities of achieving functional requirements must be known, which is out of scope for this interview as assessment of this for early stage hardware startups would be unreliable. The second quantitative metric was from Eppinger who developed the Design Structure Matrix (DSM) for management teams as a representation of complex processes during PD [37]. This metric is interesting for understanding PD complexity through tasks. However, the complexity metric I am looking for is for the physical product itself, and therefore the DSM method is not pertinent.

Over ten years later, another set of complexity metrics was reviewed in a 2012 paper by Crespo-Varela et al. searching for a quantitative complexity metric that could be used for hardware products [27]. From an initial review of fourteen different complexity metrics, they found three potential metrics that both have a mathematical formulation and applicability to hardware [9][135][78]. They compared these metrics for 21 hip replacement devices, finding that none of the metrics encompass all major complexity parameters for example product uniqueness. They then propose a new metric that adopts major aspects from the others for a more complete metric. I adopt from their new metric some parameters to use as questions to the interviewees including number of components (custom and off-the-shelf), number of functions, and innovation (through design and build outsourcing).

Another review done by Rodriquez-Toro *et. al.* introduces complexity in terms of assembly-oriented design. In this work, complexity is divided into two categories: (1) conceptual metrics usually for design including topology, geometry, and assembly, and (2) mathematical models [133]. They propose a new total complexity metric using a mathematical model which is a combination of many types of complexity: manufacturing, process, structural complexity, and sequence complexity. Total complexity is found by adding all of these complexities together with weights associated with each. I adopt some of these complexity parameters for the interview including tooling, max number of components, number of assembly operations, and material parameters.

A useful differentiation between types of complexity is also found in Schuh & Schwenk who split the origins of complexity into internal and external reasons [138]. Four types of complexity are classified: Market, product, organization, and process. For these interview, I mostly focus on product complexity, but I also include some questions on process and market complexity. For example, I add questions about how many disciplines are involved in PD and how many functions the product performs [92]. I also added market complexity parameters such as number of competitors and number and types of standard. There are many other formulations of complexity that were not used in this work due to lack of available parameter data or unsuitability [62].

Using the literature outlined above, I created a set of questions to gauge product complexity for these early stage hardware startups. Out of all the parameters adapted from the above literature, I added a few additional parameters to track including how many custom and off the shelf parts there are, whether the product has onboard logic and the number of lines of code it has, as well as if it is designed for the outdoors. The full list of 14 quantifiable parameters tracked in the interviews can be seen below in Figure 2-15.

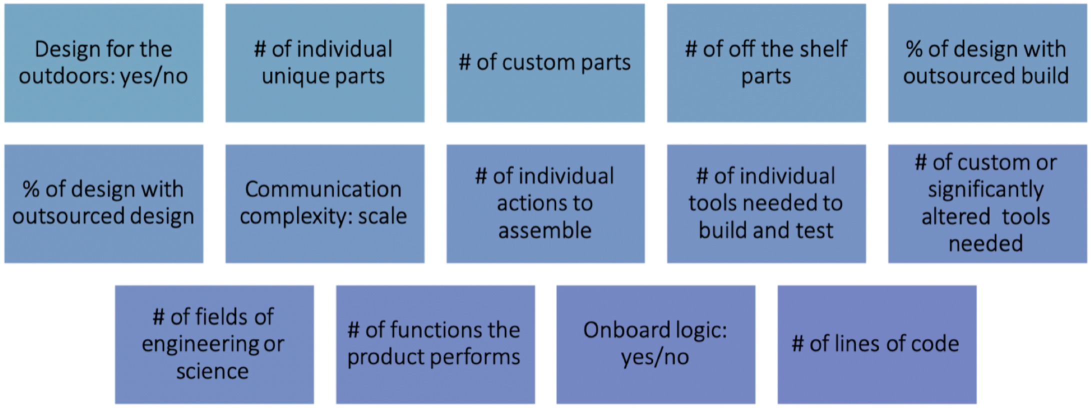


Figure 2-15: Complexity Parameters

The fourteen complexity parameters asked about in each interview as adapted from literature and modified to focus on product and process specifically.

I also developed a complexity metric as an aggregate of several parameters: number of parts, number of custom parts, percentage of design outsourced, percentage of build outsourced, whether they were designing for the outdoors, and communication complexity as shown in Chapter 3. Other parameters could not be added to the metric successfully due to lack of knowledge by some of the interviewees to answer the full set of complexity questions. Each parameter used to make the metric is then normalized on a scale from 0 to 1 and then an average is taken of all these parameters for each company. The result is a number between 0 and 1 with those closest to 1 being the most complex. The mathematical formulation is given below in Equation 2.1. In this equation, n_{pc} stands for part count, n_{cp} stands for custom part count, outsourcing the build is denoted by n_{ob}, outsourcing the design by n_{od}, n_{out} stands for designing for the outdoors, n_{comm} stands for communication complexity, and n_{tot} is the total number of variables which in this case is 6. Each of these parameters is between 0 and 1, and they are calculated as seen in the Table 7.1 below.

$$Complexity, C = (n_{pc} + n_{cp} + n_{ob} + n_{od} + n_{out} + n_{comm})/n_{tot} \tag{2.1}$$

Table 2.2: Complexity Parameter Scales

part count	0-100	100-500	500-1000	>1000	
n_{pc}	0.2	0.5	0.8	1	
% custom	0%	<50%	50-100%		
n_{cp}	0	0.5	1		
% build	0%	<50%	50-100%		
n_{ob}	0.5	0.25	0		
% design	0%	<50%	50-100%		
n_{od}	0.5	0.25	0		
% outdoors	no	yes			
n_{out}	0	1			
% comm	wifi/cell	bluetooth	radio/GPS	on-grid	none
n_{comm}	1	0.75	0.5	0.25	0

2.3.7 Prototyping

The next part of the interview is about prototyping. One of the most difficult things when discussing the PD process with a range of people from different backgrounds and educations is defining each PD step. This is especially true when discussing prototyping as there are myriad interpretations of what a prototype is exactly. Is each individual iteration a prototype, or rather is that just a version of a "prototype sequence"? To avoid this confusion, I explicitly defined each step to consistently explain to each interviewee.

For the definition of *prototype*, the interviewee is told that we are looking for *prototype sequences*. The software world has a well-known naming system with *prototype sequences* being known as Version 1.0, 2.0, etc., and individual iterations within those prototype sequences known as Version 1.1, 1.2, 1.3, etc. For hardware it can be messier as there can be virtual prototypes as well as physical prototypes, parallel subsystem prototypes, and full integration prototypes. To combat these complexities, the interviewees are prompted to think along the lines of the software scheme explained above. I also encouraged interviewees to think in the framework of established hardware prototype sequence names such as *looks-like* vs. *works-like* prototypes. With these prompts, most interviewees could divide the PD timeline into a set of *prototype sequences* which we call *prototypes* for the rest of this thesis for simplicity. These prototypes can also be designed and built in parallel and be for different sub-components of the overall system.

Another definition to consider regarding prototypes is the distinction (or lack thereof) between technology vs. product development and prototyping. *Technology development (TD)* is when a concept is still being proven out as a viable working technology, while *product development (PD)* focuses on making a commercial product out of an already proven technology. This distinction is blurry for many of the companies interviewed that are working in the technology push regime. Often some version of the technology has been proven, but perhaps not completely enough to meet the requirements of a commercial product, so some hybrid of TD and PD is being undertaken by the company. For some of the technologies, iterations have already occurred within an academic laboratory years before incorporation. In the interview, when discussing prototyping, the interviewee defines whether the prototypes specific to their company are more on the TD or PD side. The important time that I want to record is the prototyping time for a company once they incorporate and take investment funding, inducing time pressure to get a viable product. Therefore, whether they are doing TD or PD is less important than, although correlated with, how quickly they can make a viable system that either inspires more funding or leads to an exit.

Also, a distinction must be made between designing, prototyping iterations, and testing. In this work, designing encompasses ideation (concept generation) and concept selection. Whereas prototyping iterations (the build) are the physical builds of the product and testing is the evaluation of the prototype. Two types of testing are defined in the interview. One is technical testing which encompasses any testing of the performance of the system with measured metrics. For example, with batteries this could be lifetime testing, capacity testing, efficiency testing, etc. Another type of testing is customer testing where the system is tried out by potential customers for functional and/or aesthetic appeal. One difficulty with this concept is that often within one prototyping sequence, there are several "design, build, test" cycles so that the prototyping encompasses all of these steps. To keep this consistent across interviews, the prototyping sequences are mapped out on a timeline including individual questions about the times to design, build, and test. I also include open-ended questions about their design, build, and test process to capture nuances.

To accomplish the questions about prototyping and establish the timeline, I first I ask how many prototyping sequences their company has been through. Then I ask an identical set of questions for each prototyping sequence:

- Main objective for this component prototype?
- How many business days after incorporation was it started?
- How many days did it take to complete?

- How many people worked on it?
- How important is the speed of this iteration?
- How satisfied are you with your speed of this iteration?
- Was this tested on sample customers?
- How was it communicated to the audience? [verbal, sketch, photos, storyboard, video, simulation, interactive media, physical models, working prototypes, other]
- Was technical testing done on the product?
- What kind of testing was done?
- How long did testing take?

This set of questions is asked iteratively until all prototypes have been covered. The majority of companies I interview have done between 3-5 prototypes.

2.3.8 Manufacturing

The next section focuses on manufacturing. These questions stem from a set of methodologies called "design for X" where X can be reliability, environmental impacts, manufacturability, etc. The most common of these is design for manufacturability (DFM) which is extremely important for hardware startups as manufacturing costs are a key indicator of the economic success of a product. DFM includes several steps including estimating manufacturing costs and reducing component, assembly, and supporting production costs as well as considering impact of DFM on other parts of PD. [153] What plans companies have in place for manufacturing as well as their adherence to DFM principles could be indicators for how efficiently they navigate PD. Therefore I ask the questions are below:

- When did you first start to discuss manufacturing with respect to incorporation?
- Did you explicitly use design for manufacturing principles?
- What is the plan for manufacturing?
- When did you first consider standards and certification for your product?
- What processes are necessary for manufacturing and assembling your product?
- How much compromise on materials, methods, and manufacturing location has been necessary?

2.3.9 Overview

The questions posed in the overview section ask the interviewee to reflect on the PD timeline we just went through together. In this section, I ask directly the interviewee's thoughts on the major questions we are trying to answer in this study. I ask what were bottlenecks in their process and their opinions on how they might overcome these bottlenecks in future ventures. I also ask about investor pressure given slow PD.

- Has your company been pressured by funding sources to speed up design due to slow development timelines vs. short investor timelines?
- Which steps slowed you down the most? Pick all that apply.

- Which do you think could be made faster? Pick all that apply. [targeting a market segment, gathering user preferences, defining requirements, analytical modeling, computational modeling, cost modeling, concept generation, concept selection, prototyping, customer testing, technical testing, other]
- What would you have changed first in how you approached the design process to shorten the development timeline?
- What kind of strategies would you try to implement?

2.3.10 Other Considerations

One complication that arose while making the timelines for each company are market pivots. Some companies first developed a product that was unfortunately not viable in the market, so they pivot into a sector in which they can actually make money. These pivots require redesigns of varying degrees, and considerably slow down product development, but not necessarily individual prototypes. For these companies, I pick one of the products either before or after the pivot and chronicle its path.

Memory and perception also play a role with workflow mapping. As these timelines are coming from the experience of the interviewee, their individual perception of the process and an imperfect memory can distort the objective timelines. This must be accounted for in the uncertainty of the results.

Opportunity Landscape

Another quantitative set of questions asked of interview participants in addition to those enumerated above comes from the theory called Outcome-Driven Innovation, also referred to as the "Jobs to Be Done" theory. The theory states that consumers buy products specifically to get jobs done as measured through obtaining outcomes they wish to achieve with the bought object [154]. Within this framework is an "opportunity algorithm" which is a way to measure and rank innovation opportunities [155]. We adopt this method for use in identifying opportunities to innovate on and accelerate the PD process.

To find these opportunities, the interviewees are asked a series of questions about each segment in the PD process. For example, for the targeting a market step of the PD process, interviewees were asked:

> **EL:** "How important was targeting a market segment to your desired outcome? Pick among these choices."
>
> **Slide text:**
>
> - 1 - Not important at all
> - 2 - Somewhat important
> - 3 - Important
> - 4 - Very Important
> - 5 - Extremely Important
>
> **EL:** "And, how satisfied are you with the tools and processes available to you to target a market? Pick among these choices."
>
> **Slide text:**
>
> - 1 - Not satisfied at all
> - 2 - Somewhat satisfied
> - 3 - Satisfied

- 4 - Very Satisfied
- 5 - Extremely Satisfied

With the answers, each PD can be placed on a figure that visualized the overall innovation opportunity score for that PD step. The PD steps that score with the highest importance, and lowest overall satisfaction are the ones where intervention in the form of new PD tools and strategies should make the most difference. Below in Figure 2-17 is the opportunity landscape compiled from this interview. We can see targeting a market, gathering user preferences, defining requirements, outsourcing, scaling up are all growth areas.

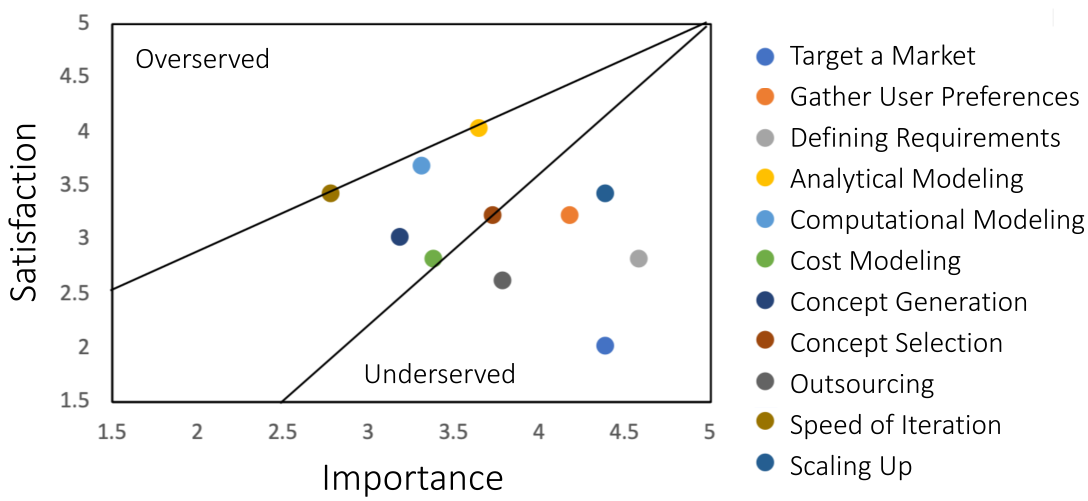


Figure 2-17: Jobs To Be Done Opportunity Landscape

Opportunity landscape mapped from the interviews showing what are underserved areas where there are opportunities to create acceleration strategies.

2.4 Interview Analysis

In this work a hybrid of quantitative and qualitative methods, often referred to as *mixed methods* is used to explore what the bottlenecks in the PD process are and how they can be overcome.

2.4.1 Transcription

Out of the 55 interviews, 50 agreed to be recorded, and were subsequently analyzed via audio file and through transcription which was done by the transcription service Rev. This resulted in 1175 pages of transcription to process. In addition, each answer was documented by the interviewer in Qualtrics survey software which was then exported into spreadsheets for analysis.

2.4.2 Quantitative Methods

The quantitative parts of the survey include the workflow mapping, complexity metrics, and jobs to be done opportunity landscape discussed above in the interview sections. These quantitative metrics are gathered as a means to generate statistics and work toward to generalizing any findings.

2.4.3 Qualitative Methods

To complement the quantitative data gathered, open ended questions about each PD step are asked. To analyze the results and find conclusive insights, qualitative research methods from the field of sociology are employed. The main method used in this work is qualitative coding which is "a way of indexing or categorizing the text in order to establish a framework of thematic ideas about it."[52] There are two main types of coding. One is data-driven (grounded) which is when the researcher allows themes to emerge from the documents with no pre-existing framework. The other is concept-driven (*a priori*) which is when the researcher applies a pre-existing framework when analyzing the documents. With either of these approaches, coding is an iterative process of code refinement and comparison to the source text [142].

In this work, we used a mixed approach of both concept- and data- driven coding. As a trained engineer and the interviewer for the study, I employ concept-driven coding with pre-existing hypotheses and framework. My collaborator Andre Buscariolli, a trained sociologist, does data-driven coding with no pre-existing framework. Through a series of meetings, the codes found in common by both coders (Andre and myself) or mutually agreed upon through compelling evidence are pursued. Through this work, over a dozen codes were found for the 55 interviews, and were iterated upon until several specific coded themes developed. There are two kinds of codes used in this work. There is data-driven or grounded coding that allow themes to emerge from the documents. There is also concept-driven *a priori* that applies pre-existing theoretical frameworks to analyze the documents [52]. Codes found for this work include:

Data-driven Codes

- Fast vs. Slow Iteration Tension
- Merge and clash of technology and business aspects of PD
- Manufacturer Relationships
- Investor Relationships
- Customer Relationships
- Natural vs. Structured process
- Practiced vs. Taught

- Abstract vs. Concrete

Concept-driven Codes

- What they would or would not have done differently
- Slowest steps, or any major pain points
- Lack of manufacturing knowledge
- Lack of targeting a market
- Emotional attachment to design or application

2.5 Hypotheses

The stated goal of the interview done for this thesis is to map PD timelines, determine pain points in PD, and discover what could accelerate this process. With over a dozen qualitative codes and quantitative data collected, a set of hypotheses develop toward this goal. I separate these hypotheses into two categories: operational and technological. The operational category pertains to parts of the PD process "relating to the routine functioning and activities of a business or organization."[140] Whereas the technological category relates specifically to the product and its design, functions, prototyping, testing, etc. These hypotheses are enumerated below.

Technical Hypotheses to Test:

1. Prototyping is the longest development activity.
2. Complexity of the product correlates with time to prototype.

3. Startups to date rarely employ state of the art computational tools for design, build and testing processes.

Operational Hypotheses to Test:

1. Bringing structure into the process at the wrong time in product development causes delays.

2. Successful relationships with customers, investors, and manufacturers accelerate product development.

Using these two designations and the extensive data collected from the interview, analyses are presented in the next three chapters to test these hypotheses, determine pain points in PD, and develop paths to acceleration.

Chapter 3

Interview Analysis I: prototyping, product complexity and innovation models

In this chapter, I examine what hinders successful cleantech commercialization and how the community can overcome these obstacles through mixed-methods analysis of interview data. I test two technical hypotheses in this chapter developing two findings: First, I show that prototyping is the longest product development process. Second, I show that product complexity does not correlate to prototyping times which suggests the existence of a systematic rate-limiter in PD independent of the product itself. Then, to understand what this rate-limiter might be, I explore a third operational hypothesis, using qualitative labels to investigate the impact of innovation models on cycles of learning. I find that a flexible, organic innovation model can accelerate early-stage innovation, while a structured PD approach is preferred for later-stage innovation.

3.1 Product Development Status Quo

Aggregating all of the timelines from the interviews, I find the amount of time in years each PD step takes to complete as seen in Figure 3-1.

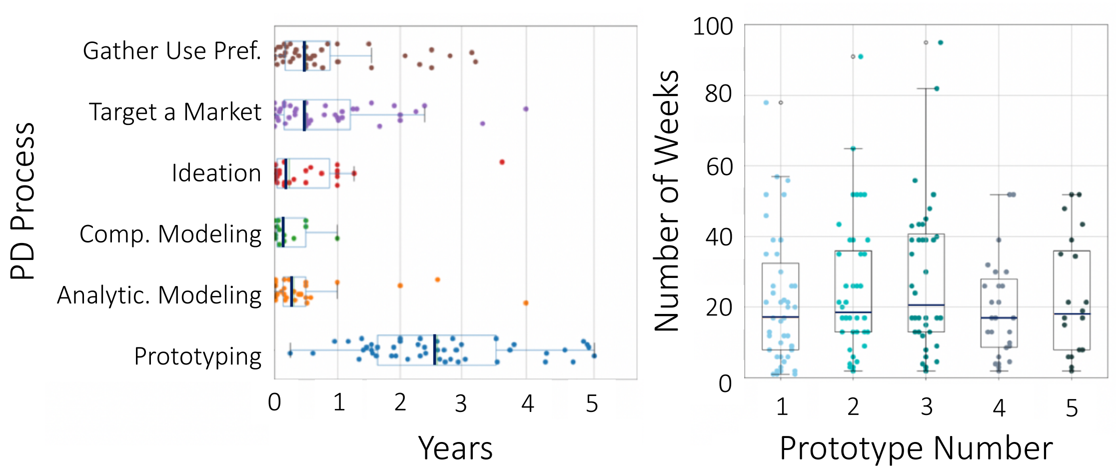


Figure 3-1: Time Taken for Product Development Steps

Sample size, n = 55, Left: Number of weeks taken to complete each PD activity. Right: Times per prototype for each company in weeks.

Total prototyping time is the longest PD step at around 2.5 years for 5 prototypes while the remaining PD activities have a median of less than one year. Gathering user preferences and targeting a market are next in length with medians of over half a year in total time. Plotting the amount of time per prototype for prototypes 1 through 5, I find a median per prototype between 17.5 and 20.5 weeks. Totaling 5 prototypes times 19 weeks per prototype is 1.8 years in total which is 0.7 years less than the median of 2.5 years. This indicates some period of time in which the company is not prototyping between iterations. For the first three prototypes the time to prototype grows slightly with each occurrence. However, overall the amount of time it takes to prototype stays close to consistent for each iteration, defining a "characteristic prototyping time" of about 19 weeks per prototype.

I also wanted to understand how the CEO's and CTO's perceived how long each PD step took, so I asked the below set of questions to track these perceptions. The answers are displayed in Figure 3-3.

> **EL:** What PD step slowed you down the most?
>
> **EL:** What PD step do you think could realistically be made faster?
>
> **Options for interviewee to choose from:** Targeting a market segment, Gathering user preferences, Defining requirements, Analytical modeling, Computational modeling, Cost modeling, Concept generation, Concept selection, Prototyping, Customer testing, Technical testing, Other

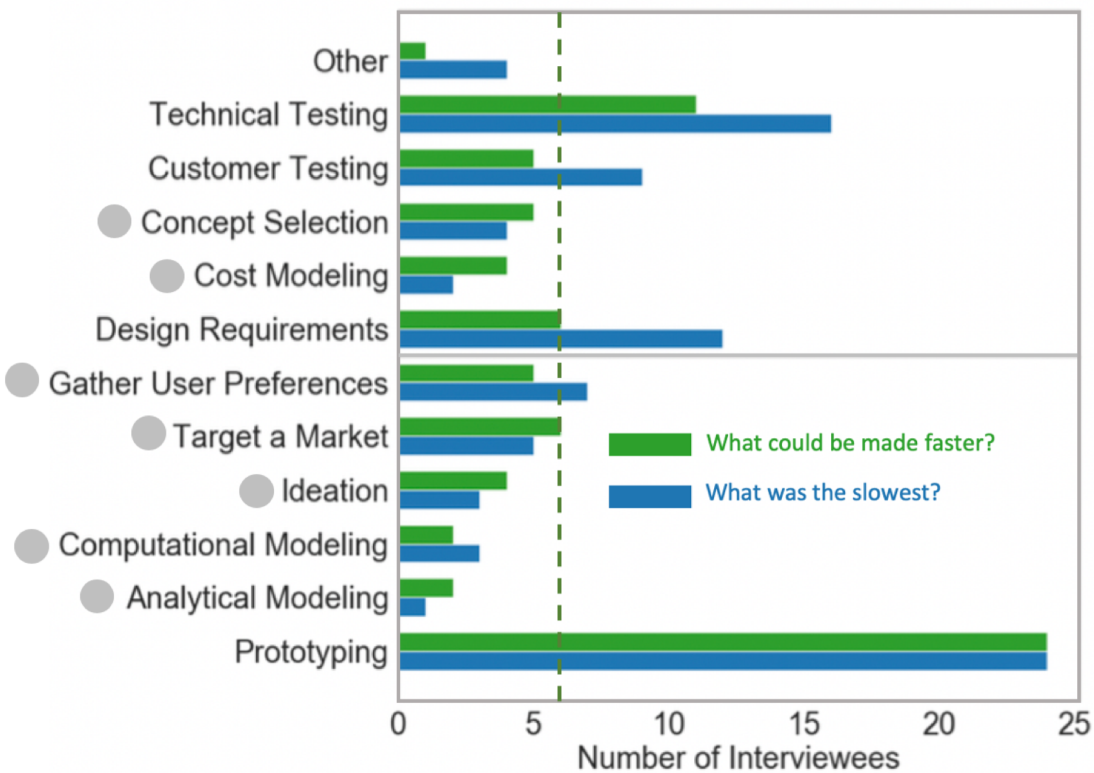


Figure 3-3: Perceptions of Interviewees about Product Development Times

Sample size, n = 55, Interviewee perceptions about PD process timelines. (The horizontal line in the figure separates the PD quantified (below line) and those that could not be quantified in Figure 3-1 (above line).)

As seen in Figure 3-3, a majority of interviewees believe that prototyping is the slowest PD step, matching reality. Also, they believe uniformly that prototyping could realistically be made faster. There is also less confidence by the interviewees in speeding up any other PD activities. There are < 6 interviewees that have confidence in making any other steps faster as is denoted by the dotted line in Figure 3-3. The only exception to this is technical testing with 12 people confident that this could be sped up in some way.

One way to categorize these perceptions is through the labels of "soft" and "hard" aspects of PD and how long they take. "Soft" development activities, meaning anything that doesn't involve the physical product, includes concept selection, generation, all modeling, gathering preferences, and targeting a market. These are denoted in Figure 3-3 with a grey circle. "Hard" development activities deal with the physical product such as developing design requirements, prototyping, customer testing and technical testing. In Figure 3-3, the soft PD aspects are not pointed to as the slowest development activities as often as the hard PD aspects. Also, there is more confidence by interviewees that these soft PD steps could be sped up with implementation of different strategies or processes, whereas fewer interviewees believe that the speed of hard PD aspects could be altered. There are two exceptions to this: computational modeling and gathering user preferences. In both cases less interviewees had confidence these steps could be sped up than those that thought it was the slowest activity.

From the overall times recorded for each PD step and the perceptions that the interviewees have about them, I focus on another secondary research question: Are there common factors among companies that correlate with how long PD takes? To explore this question, I focus on factors that can affect prototyping as that longest PD activity, and reduction of prototyping time could give the largest overall PD acceleration.

3.2 Product Complexity and Prototyping Times

One hypothesis for investigation when analyzing PD times is that complexity is positively correlated with time to prototype, meaning the more complex the product, the longer it takes. Intuitively, a more complex product would take longer to design, build, and test.

As described in Chapter 2, a set of complexity questions are asked in the interview to gather key complexity parameters. I plot several of these parameters against the median times per prototype in weeks. I also devise an aggregate of these parameters into one complexity metric and plot that versus time to prototype which is outlined in bold in Figure 3-5. The complexity metric formulation is discussed in detail in Chapter 2.

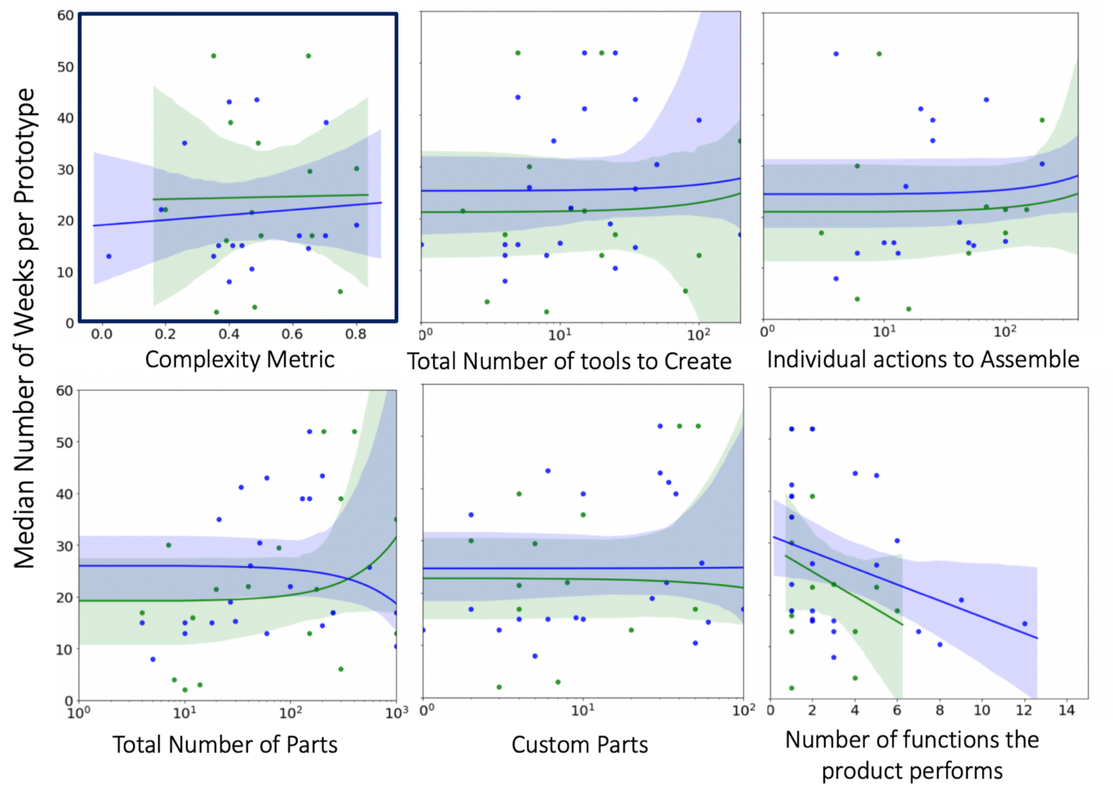


Figure 3-5: Complexity Metrics vs. Average Time to Prototype

Plotted with ordinary least squares regression trend lines. Green is for Cleantech and blue is for other companies. In the top left is the complexity metric that takes into account several complexity parameters: part count, number of custom parts, percentage outsourced of build and design, and design for outdoors.

The major finding from Figure 3-5 is that there is no significant correlation between how complex a product is and the time it takes to prototype with these parameters adapted from literature. This is a surprising result as intuition would suggest that a more complex product would take longer to prototype. The only trend found in these plots is with the number of functions the product performs. This could be due to several things, one is that for products the interviewee conceives of as simpler, there is a tendency to enumerate more non-essential functions, whereas for complex products, the interviewee focuses on the one or two main functions. To validate this trend a more rigorous definition of essential functions vs. other functions is needed. In these figures, green represents Cleantech and blue represents other types of technology. The curves for both companies are fairly uniform showing that both types of companies follow similar complexity trends with prototyping times and there is little to distinguish Cleantech from the others.

Due to the lack of correlation between complexity and time to prototype within these companies, I continue to search for drivers of prototyping time. To do this, I use qualitative labels to investigate the impact of innovation models on cycles of learning.

3.3 Structured vs. Organic PD process

One qualitative grounded code that emerged from the analysis deals with the interviewees placing their development process on a spectrum from organic and natural PD to highly-structured PD. Section 3 of the interview on *Defining Requirements* prompted many responses pertinent to this spectrum. Every interviewee was asked this series of questions specifically about engineering requirements as listed in Chapter 2. Responses about engineering requirements were varied throughout the interviews, but a clear tension was apparent between a more natural approach and more structured approach. For example some companies describe their design decisions mentioning the lack of structure:

EL: "So, did you use traditional engineering requirements?"

C.6: "No. We didn't do anything traditional. It was pretty organic."

EL: "Okay. So, would you say official, loosely worded, or no requirements were discussed?"

C.6: "I would say the middle one. Less official, loosely worded. Just like, 'We kind of need this. Let's try it.' We built this hacky solution and fixed it. Yeah."

EL: "Cool. What, if any types of requirements were discussed in-depth?"

C.6: "Just functional. Oh, and interface, I would say. Everything else, we prayed ..."

This exchange demonstrates one approach to PD that is natural and organic. No formal requirements were used and there was a description of things "just happening" or evolving naturally as the team worked toward designing and building prototypes. These descriptions are common among the startups interviewed, with descriptions such as "going with the flow," letting the design "evolve," and undertaking "organic" or "natural" processes.

On the other end of the spectrum were companies that approached PD in a rigorous, structured manner. There were a few flavors of these companies: those with an investor or grant that imposed structure, those with experience in industry using structured PD, and those that had recently practiced structured PD in a university setting. For example, one company working in medical device design explained:

EL: "Were traditional engineering requirements used?"

C.5:"It was imposed, right? It's required because it's an FDA regulated product. So there's no optionality there. If you want to bring something to the market, you have to because the FDA requires it."

This enforced structure can be beneficial to some companies. For example another company expressed that the structure mandated by their government grant in the form of milestones was a useful strategy:

> **EL:** "Looking back, would you could spend more or less time on requirements creation?"
>
> **C.8:** "On the requirements creation. No I don't think so. I mean it definitely seems like a necessary part of the process and it's good to have those [grant] milestones to try and hit. So, I mean, I think it's a pretty good strategy."

In above interview excerpts, the tension between natural and structured PD models is evident. In the following sections I give evidence of both types of strategies and how companies used the different models, whether they wish they had done something differently, and if they switched between or blended the two models during PD. Through this analysis, I develop some potential best practices and operational strategies for startups to accelerate PD through intentional use of structured or natural innovation models.

3.3.1 Definitions of Natural and Structured PD

Before detailing the analysis, I will define natural innovation and structured innovation as I am using it in this work. Natural innovation is a flexible process in which prototyping iterations evolve following the intuition of participating engineers generally without rigid planning or requirements. Natural innovation allows for free-form ideation, rapid switching between designs, and exploration of a comprehensive design parameter space. Structured innovation is an ordered process in which prototyping iterations follow prescribed and codified plans including defined engineering requirements with procedures in place for altering plans. Structured innovation creates order that ensures the design meets the functional and cost targets of the product, can be manufactured, and allows for communication of the design and process.

3.3.2 Arguments in Favor of Structured PD

Several companies expressed that they wished they had brought more structure into the PD process earlier. For example, one company details:

> **EL:** "If you could go back in time and do things differently, would you spend more or less time on requirements? Could you speed up the process? If so, how?"
>
> **C.9:** "Actually, I would spend more time on requirements."
>
> **EL:**"Why?"
>
> **C.9:** "In the process, we made a number of different prototypes, which I think looking back is not necessary, if we had proper like getting the detailed requirements already done. That could also speed up the process."

This is an example of where investment in structure might pay off in the long run, actually speeding up the overall PD process. Another company had a similar take on slowing down to define rigorous requirements in an effort to speed things up overall. When asked what they would do differently if they were to start the company again:

> **C.15:** "Well, the big thing would be getting in front of your customer and using that data to then have a rigorous requirements definition... Then hopefully, yeah. You have a very informative requirements document and then I think the prototyping would be way faster, yeah. Because you're not going down wrong paths."

This is especially true for companies outsourcing the build of their prototypes. One company explains this:

> **C.2:** "We started with less specific requirements and it was a disaster. When we got the first prototypes from them, [they were not right]."
>
> **EL:** "Would you spend more or less time on requirements creation?"
>
> **C.2:** "We would have done it earlier. I think we lost [time], just because of issues with suppliers, nearly half a year."

3.3.3 Arguments in favor of Natural PD

Despite all this advocacy for structure, other companies explained how too much structure can be a problem. For example, one company would spend less time on requirements creation:

> **EL:** "If you could go back and do things differently in the defining requirements section, would you spend more or less time? Do you think you could speed the process up? Would you change anything?"
>
> **C.13:** "I probably would spend a little bit less time arguing about whether it should be this value or that value cause really at this stage, it doesn't matter. You just have to pick something and go with it. You're going to learn how to adjust it... One of our early angel investors gave me a piece of advice that is a soundbite motto but I found very useful. He basically said, 'There's no good decisions and bad decisions. There's just decisions and then you work to make them good.' So it's basically saying don't waste time analyzing it to all hell."

Another example of the need for balance comes from Company 18, who recognized the need to not be so attached to a certain requirement as they may have to change it many times in the early stages of PD process.

> **EL:** "Did you use traditional requirements? Like, should, shall, would. Or, did you loosely worded ones? Or you just didn't have requirements?"
>
> **C.18:** "I think it was loosely worded, because all of these were like sort of an aggregate of casual conversations I've had with people after a conference, drinking, at dinner, etc..."
>
> **EL:** "So, You did use [loosely-worded] traditional requirements. How important did you find finding requirements to your outcome?"
>
> **C.18:** ... "I'd be middle-of-the-road on that, because you can design to certain requirements, but then there's other things that you thought you were going to be able to achieve and then all of a sudden you can't. So, you don't know a priori what the technology challenges are going to be."

And a last example cautioning against being structured too early comes from a CEO describing what happened to his last venture that eventually failed. He explained how they got too structured too quickly and how that occurred due to over reliance on customers knowing all the requirements needed:

> **C.27:** [Talking to customers, we asked them to] "... pick an objective, explain to me what are its KPIs [key performance indicator], it's our job as engineers to define the means through which we achieve a KPI. So that's not what I need from my customer, what I need from my customers is a definition of a KPI and then when I formulate a device that should

> hit those KPIs. That's when I started hearing the things that I wouldn't know to ask."

This shows that settling in on one requirements list too early is a bad choice, as he further elaborated:

> **C.27:** "Exactly, that [iterating on requirements] was something that we stopped [at my last company] too early. So we brought in someone who was from a very, very big company, technical lead to be like there's an adult in the room style control. But, it was the wrong point in the company's life cycle. [Before that] there was so much speed that we had by just building small pieces of the thing that we envisioned. Not the whole thing, you waste time and money, but something that gives a flavor of the concept and just showing it to people and then writing down everything they said. And, so we probably stopped doing that [iterating on requirements] at [my old company] a year earlier than we should have."

3.3.4 Finding Balance Between Natural and Structured PD

As shown in the examples above, there is a tension around when and how necessary it is to bring structure into the process. Balance between the natural and more structured is important as what serves the company well at the beginning may not serve it well later on. Each company falls somewhere on the spectrum from natural approaches to more structured approaches. Using analysis from the interviews, I developed a method for placing companies on this spectrum seen below in Figure 3-7. Each time an interviewee mentions in the interview one of the things on the spectrum in Figure 3-7, they are assigned one point at that position on the spectra.

Then, the overall totals are summed, normalized, and a number between 0 and 1 is calculated placing the company in one of the 3 categories: natural, hybrid, and structured.

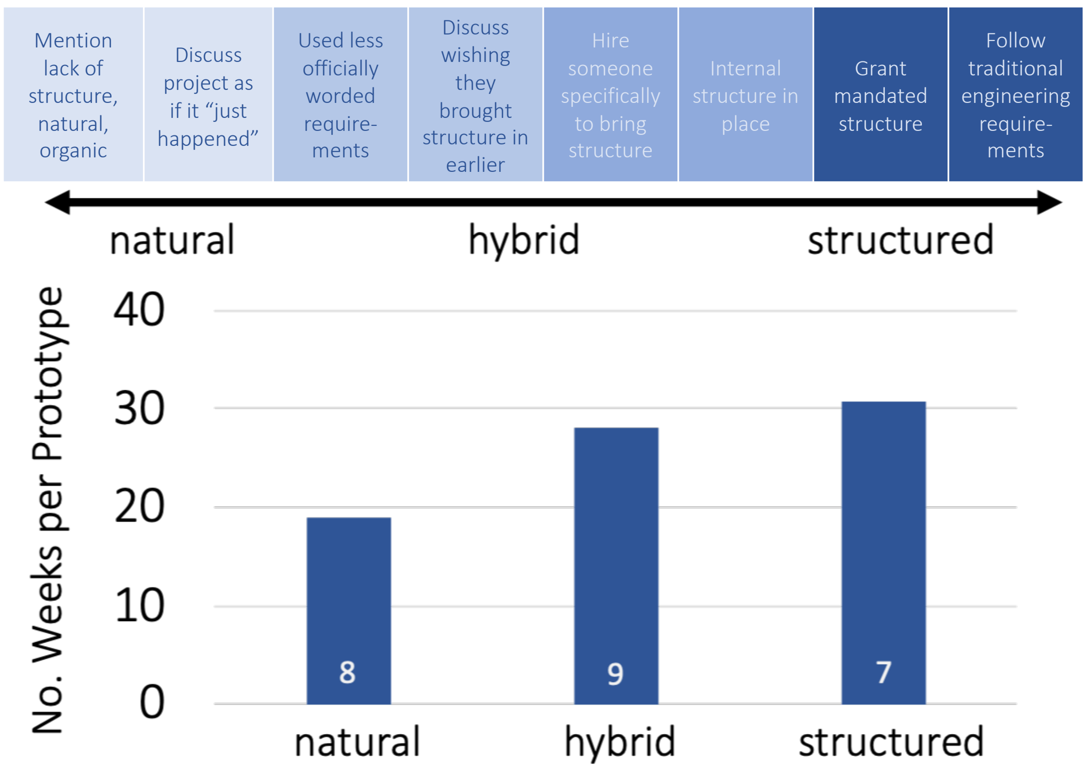


Figure 3-7: Natural to Structured Innovation Spectrum

Top: Spectrum from natural to structured process with criteria for categorization of companies along that spectrum. Bottom: Startup companies on the spectra vs. how many weeks it takes to complete one prototype on average.

As can be see in Figure 3-7, the companies using highly structured processes for prototyping have an average of about 31 weeks per prototype, while companies using natural processes average around 19 weeks, about one-third less time. This result points to a more natural process being a better choice if prototyping quickly is the only goal. For the first few prototypes this is likely the best approach, as structure can bring paperwork, extra tasks, and careful evaluation which explains the much longer prototyping time. However, at a certain point in the life cycle of a company, structure can actually accelerate PD as was seen in the section with arguments in favor of structured PD. Therefore, there is a balancing act that startups must perform to get through prototyping efficiently, having a natural process enough to move quickly and creatively at first, but bringing in structure enough to not waste time in the long run.

One CEO explained this tension and his compromise between these two extremes in a hybrid approach:

> **EL:** How important was defining requirements for you?
>
> **C.26:** "It didn't happen like I sat down and I came up with the requirement. While making the thing it evolved... It's a compromise because you can perfect one design and make sure that it's going to work in [the] first shot. But the other approach is just to do it fast. Okay, let's get it, try it, fix it, fix it. So what I'm doing is the second one."

3.4 Case Study of Introducing Structure Late

There is a pertinent example from the interviews of a company bringing in structure too late which demonstrates how this can drastically slow down PD. Below in Figure 3-9, the timeline of this company is shown. For this companies, the first five prototypes had a median prototyping time similar to that found for all companies earlier in this chapter, around 5 months. After this prototype however, there was a total redesign for prototype 6 that fell victim to both overengineering and feature creep that took a total of 1.5 years to finish. Overengineering is when a product is designed to be overly complex, having more features or greater robustness than is necessary for its functions leading to inefficiencies. Feature creep is the expansion of product requirements during prototyping by adding features beyond the original scope of the product.

According to the CEO brought in to overcome these issues after prototype 6:

> **C.44:** "Unbeknownst to the sales people that were trying to sell [the product] and to the board of directors, [the company] undertook a top to bottom redesign of the product. It took over a year before another unit was in the field."
>
> **EL:** "Did it fix the problem?"
>
> **C.44:** "No. Actually, nothing was better. Everything was worse. It was more complicated, more expensive, more difficult to make, more sources of failure."

After the new CEO was brought on, there was a year-long reversing of the over-complicated prototype, resulting in over 2.5 years of development time that could have been shortened or done away with completely as seen in Figure 3-9:

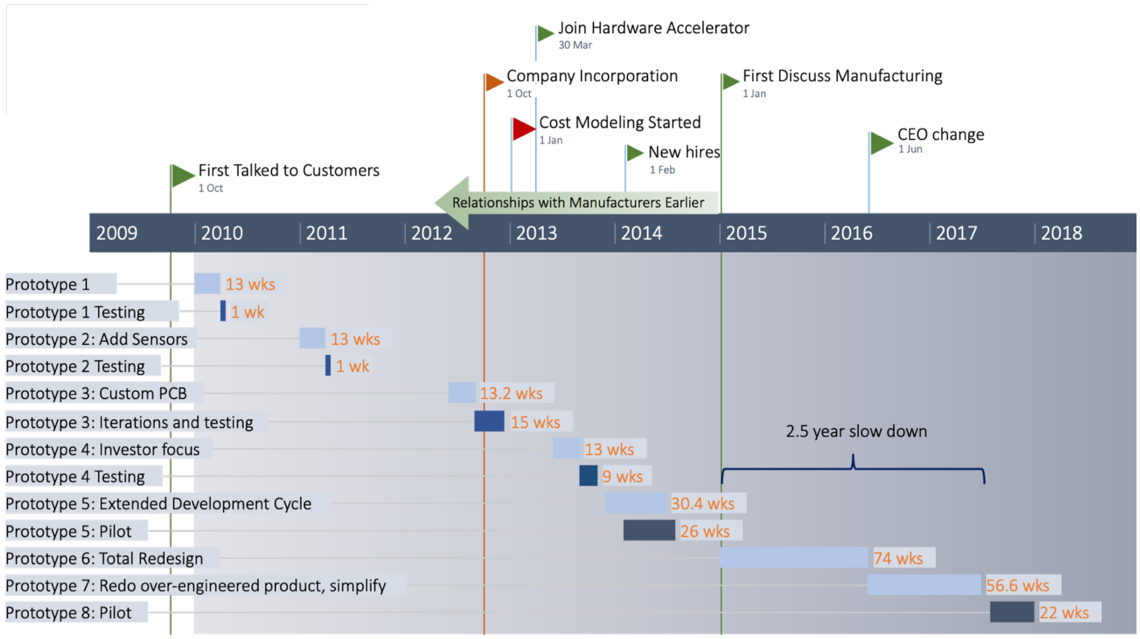


Figure 3-9: Company Timeline Example of Overengineering Slowdown

Timeline for company that struggled with overengineering and feature creep which slowed the PD down by over 2.5 years.

In this example, the first 5 prototypes were done relatively quickly. After this, a lack of explicit requirements emphasizing design simplicity, maintainability, and other key requirements, the product become overly complicated. If the company had brought in such structure after the first 2 or 3 prototypes, this may have been avoided. At the point where technology, implementation, and market had collapsed into one product goal like in Figure 3-11, bringing in structure might have helped with identification and prevention of such feature creep or overengineering.

This example in Figure 3-9 demonstrates that structured innovation, although slower overall as seen in Figure 3-7 can actually accelerate PD if brought in at the right time. For example what is not shown in that figure is how many overall prototypes must be done. If a company is completing a prototype per week, but does not complete a market ready product until after 200 iterations, this is more time consuming than a company doing a prototype every three months but only needing 5 iterations. Bringing in structure can reduce the overall number of prototypes that must be done.

This example in Figure 3-9 also supports the hypothesis of complexity not being correlated with prototyping time: There is a tendency toward perfectionism and overengineering with simpler products as compared to more complex products. The reasoning behind this hypothesis is that if a product is known by the team to be complex, there is a prerogative to do "quick and dirty" prototyping and decision making due to the constant pressure to get something working. However, for products seen as less complex or "simpler" by the team, there is a tendency to try to make a prototype perfect on the first go rather than just getting something working. Also, there are indications from the interviews that for simpler products, there is a risk of "feature creep" where additional features are added to the design that are not fundamental to the core product functions. This hypothesis could be further studied and expanded into more strategies to prevent less complex products from taking an unnecessarily long time to prototype. This is a promising future research direction for this work.

3.5 Transition from Natural to Structured PD

Given that bringing structure in at the right time could potentially accelerate overall product development, an important question becomes, how do companies know when to migrate from natural PD to structured PD? Knowing and implementing the answer to this question could speed up PD. Through insights from the interviews I determine several best practices for when to bring structure into PD to accelerate prototyping times.

3.5.1 Team Expansion

One point at which bringing structure in PD is advised is when the team expands beyond the first founding members. For example one company CEO, who first approached design naturally said:

> **EL** Yes, I am. Do you use traditional design requirements?
>
> **C.15:** "So we kind of go through the prototypes quickly instead of having a really rigorous computation of all the requirements required... [We] made some decent progress but then when I brought in other people... I noticed that that process just doesn't work for certain people... And then I realize that I need to bring in the more formalized project management structure. It's through that that we will write down the different design requirements."

The need for structure in this case is mostly about communication and expectations. With new team members that must be brought up to speed and understand company expectations, a structure is crucial.

3.5.2 Working with Outside Partners

Another point at which structure should be brought in is when communication with partners becomes necessary. Several companies expressed that a lack of documentation and structure made initial interactions with manufacturers or other outsourcing firms inefficient and a time sink. For example, one company explained that an entire prototype was wasted as their outsourcing partner did not understand what they verbally described and made something unworkable. After documentation was introduced, this problem was overcome. Another example of this comes from Company 28 in this exchange:

> **EL** "If you could design or build anything differently, or outsource more or less would you have done something differently?"
>
> **C.28 CEO:** "We would have worked with our contract manufacturer and brought him into the design sooner... Just documentation. It's an investment that pays off. The more you do the better. And it's never too early to give the design to your contract manufacturer once the industrial design is done."

Without structure, communication was ineffective between the stakeholders in these examples. Structure is shown to be incredibly important when bringing in outside partners who must understand the intricacies of the product and agree to the conditions of PD.

3.5.3 Iterative Innovation Model

So far I have highlighted two points in PD where structure should be brought in. Now, I will place this natural to structured framework within an innovation model found in literature to give further insight for companies as to when structure becomes important. Fitzgerald *et al.* developed an innovation model in *Inside Real Innovation* that has parallels to the natural to structured spectrum. In this work, a model of innovation is presented for both fundamental (disruptive) and incremental (sustainable) innovation containing an iterative process between technology, market, and implementation.

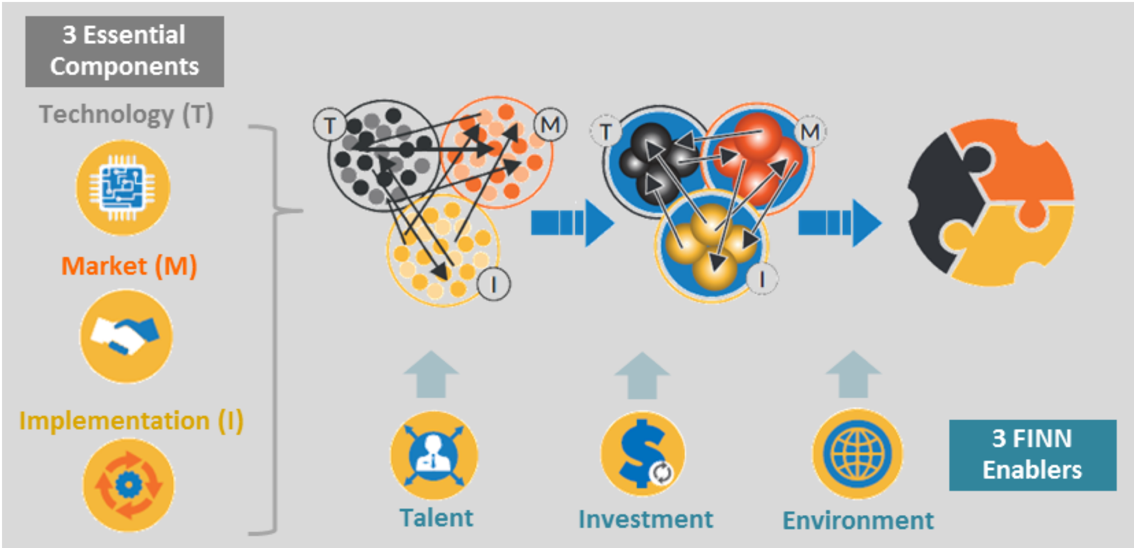


Figure 3-11: Iterative Process of Fundamental Innovation

The iterative innovation process showing iteration of technology, implementation, and market until a fit is found [43].

In Figure 3-11, as the startup develops, these iterations collapse into an implementation of a specific technology for a certain market [43]. Along this axis, I argue for the bringing in of structure gradually until a full structure is in place at the point where the three circles come together. Once technology, implementation, and market have been selected in this model, the three indicators of when to bring in structure as described in this chapter have likely already occurred or are imminent: the company brings in new people, begins serious collaboration with manufacturers and outsourcing partners, as well as the price for overengineering or feature creep is unsustainable. This model therefore gives a point in the process before which structure should be implemented. In Figure 3-11, this is before the final arrow to the puzzle pieces. It is important to note that Figure 3-11 are steps in an innovation process which does not encompass all of product development. There are many PD steps including more prototyping iterations following this last part of the innovation process in this figure in which structure is essential, and before which natural or organic innovation might be preferred.

3.6 Conclusions and Future Research

In this chapter, I examine what hinders successful cleantech commercialization and how to overcome these obstacles through mixed-methods analysis of the interview data. I show that prototyping is the longest product development process and therefore accelerating prototyping would have the largest impact. I find for the startups interviewed that the first 5 prototypes take a median of 2.5 years, and each prototype takes a median of 19 weeks to complete. I show that there is very little difference between the median of cleantech vs. the other companies interviewed in amount of weeks to prototypes. This indicates that, if cleantech companies are taking longer to get to market as suggested by literature, then this is due to having to complete more prototypes or other market and PD factors, not that each individual prototype is taking longer.

Then, I investigate what aspects of hardware companies effect prototyping timelines. I show that product complexity does not correlate to prototyping times which suggests the existence of a systematic rate-limiter in PD independent of the product itself. This was a surprising conclusion, as time to prototype would intuitively scale with complexity. To explore this finding further and continue searching for what effects prototyping timelines, I investigate the impact of innovation models on rates of cycles of learning. Using qualitative labels to place companies on a natural to structured innovation model spectrum, I find that a flexible, organic innovation model can accelerate early-stage innovation, while a structured PD approach can be preferred for later-stage innovation.

I further analyze three potential indicators of when companies should inject structure in their PD. The first is when the company begins to bring in new employees and needs baseline structure for efficiency gain where before it would be unnecessary. Second, I find that when companies begin to outsource part of the design or build, or begin to work seriously with manufacturers, structure becomes more necessary to not waste time. Lastly, I determine a point in the iterative innovation timeline from Fitzgerald *et al.* before which natural PD and after which structured PD is preferable.

I also examine a case study of this from one interview in which I find that structure could be helpful for overcoming PD problems such as overengineering and feature creep which can plague design. In this case study, I find that although dependent on the company and product, bringing structure in after the 2nd or 3rd prototype could help prevent the pitfalls of staying in a natural PD regime too long.

In the next chapter I add a fourth element to accelerating PD regarding stakeholder based operational strategies rather than physical product-based strategies. In that chapter, explore the hypothesis that successful relationships with customers, investors, and manufacturers could accelerate product development.

Chapter 4

Interview Analysis II: Relational Requirements with Customers, Investors, and Manufacturers

In this chapter, I test the hypothesis that successful relationships with customers, investors, and manufacturers accelerate product development. Through analysis of the interview data, I find that interactions with investors, manufacturers, and customers are commonly pointed to by startups as places where they made mistakes and PD was slowed down. I find some best practices for startups to potentially adopt, and I propose that codifying some of these best practices as requirements in the traditional sense might be a promising strategy to accelerate PD timelines.

4.1 Introduction and Motivation

Engineering requirements, as defined by the *Fundamentals of Systems Engineering* class at MIT, "describe the necessary functions and features of the system necessary to conceive, design, implement and operate."[29] [1] Requirements focus on what needs to be achieved, not how to achieve it, so as not to dictate or limit the design space. Establishing requirements appropriately is critical to engineering success as missing or over-ambitious requirements cause cost overruns and missed deadlines. Types of requirements include functional, performance, interface, environmental, reliability, safety, maintainability, and more.

Technical requirements creation and execution are fundamental to the engineering practice. Four to five decades ago, engineers often would not create the requirements which they were bound by, instead receiving them from higher ups in a company hierarchy and executing design and delivery of a part or product as mandated.[109] However, this top down style of engineering has evolved dramatically with the rise of CAD, instant communication, and globalization starting in the 1980's becoming ubiquitous by the 2000's. Often engineers at all levels need to work with customers, manufacturers, and investors during the development process especially in the startup context. However official requirements addressing the relationships between a startup and its stakeholders are not codified or taught in the same way as technical requirements. For example, the Accreditation Board for Engineering and Technology, Inc. (ABET), which is the board responsible for ensuring degree programs fulfill requirements of engineering degrees does not overtly require any relationship building material in the curriculum. The focus is on the technical material

[1] There are several standards for requirements from NASA, the International Council of Systems Engineering (INCOSE), International Organization for Standardization (ISO), and International Electrotechnical Commission (IEC).

with purely technical subjects specifically listed as mandatory [25].

Although official education on relational requirements is missing within many engineering certifications and degrees, within literature stakeholder relationships have been studied extensively.

Since the late 1980's there has been research on successful stakeholder relationships creating value for companies by conferring competitive advantage and/or better performance [156][5][53]. In his book, *Strategic management: A Stakeholder Approach*, Freeman introduces stakeholder theory. This theory in part says that "to successfully create, trade and sustain value, a business must engage its stakeholders."[46]

Freeman defines a stakeholder as "any group or individual who can affect, or is affected by, the achievement of a corporation's purpose which can include customers, suppliers, employees, communities, and financiers [45].[2] Both cooperation and continuous communication (responsiveness) with stakeholders have been encouraged as strategies to increase performance of startups [159][127]. The amount of research dealing with stakeholder theory in a startup context is small compared to that of larger companies [2][8].

In one of the few empirical studies, Du and Kadyova through 8 semi-structured interviews, find "startup companies should have focus in customer and important service suppliers which could help with their product, market, and sales development and contribute to financial growth more directly."[32]

Within startup community literature there has also been a surge of publications encouraging stakeholder engagement, for example Steve Blank's work on how to build a successful startup. Blank, who has written several books on this topic including *The Four Steps to the Epiphany* and *The Startup Owner's Manual*, emphasizes the importance of customer relationships both physical and online for testing and

[2] In this thesis I focus on customers, manufacturers (a type of suppliers), and investors (financiers)

validating business and product hypotheses [13].

This emphasis on customer feedback over intuition is one of the main tenets of the lean start-up, a concept championed by Eric Reis in his book *The Lean Start-Up* published in 2011 [129].

In 2013, Blank enumerates the key tenants of a lean startup as experimentation over elaborate planning, iteration over waterfall design, and customer interaction over intuition. While these concepts are beginning to be adapted to business school curricula, and have "taken root" in the start-up world, this has not "gone totally mainstream.. consisting mainly of a buzzword that's not yet widely understood, whose implications companies are just beginning to grasp."[13]

Despite the extensive research done in this area some of which is outlined above, I find in these interviews that these startups still make significant mistakes in stakeholder relationships that cost them time and money. One problem may be that these relational requirements are not codified alongside technical requirements when engineers design products. This lack leaves the companies open to slow downs, missteps and potential failures due to these missing clear relational requirements. As these relationships with customers, manufacturers and investors are critical components to development, I find that codifying these relationships in requirements documents just like the technical requirements could accelerate PD. Furthermore, to implement this broadly in startups and companies, relational requirements creation and implementation could be taught within universities as another required part of the engineering curriculum.

In this chapter, I outline a set of relational requirements found through qualitative coding analysis of the interviews described in Chapter 2. They include three categories (or startup stakeholders): investors, manufacturers, and customers. The addition of these relational requirements is seen as a strategy to accelerate PD by avoiding the common missteps caused by incomplete or untimely interactions with these three stakeholder groups.

4.2 Identifying Relational Requirements

Through coding of the interviews, independent identification of the relational requirements code was made, followed by subsequent agreement of the code by myself and collaborators from the University of California, Santa Barbara Department of Sociology, PhD Candidate Andre Buscariolli and Professor Geoffrey Raymond. I analyze this code through each of these stakeholder groups in the next sections.

4.3 Customer Relationships

I begin by exploring relational requirements with customer relationships. The relationships between customers and the companies that build products for them has been evolving rapidly since the 1980s along with globalization and technology advances. Within the engineering design world, concepts such as user-centered design (UCD), coined by Donald Norman in the 1980s, started to capture the changing relationship between engineer/designer and customer/user. UCD grew in popularity with the books *User-Centered System Design: New Perspectives on Human-Computer Interaction* and *The Design of Everyday Things* which outlined principles of good design focused on customer/consumer input. The field of UCD has since created models and processes for implementing these principles including cooperative, participatory and contextual design as well as quality function deployment [59]. Many companies, both hardware and software now use some form of a UCD process during PD including the general steps outlined below:

1. Identification of primary users, reasons for use, requirements, and environment of use
2. Specify product requirements
3. Devise and develop solutions through iterative prototyping
4. Evaluate through customer testing of product

Within universities, these principles have been trickling into the engineering curriculum since the 1990s. In the Product Engineering course at MIT (2.009, Product Engineering Processes), the course textbook by Ulrich and Eppinger, *Ulrich2015* has a chapter on identifying customer needs as an essential step in PD processes. Students in this course develop customer relationships and turn user requirements into specifications. However, not all engineering programs require such experiences as discussed in the introduction, and customer relationship requirements are not taught concretely like technical requirements. Through analysis of the interview study results, I consider the addition of these customer relational requirements into engineering curriculum as a strategy for PD acceleration within startups.

4.3.1 Customers vs. Users

A further complication of customer relationships and UCD is the distinction between business to business (B2B) and business to customer (B2C) companies. B2B companies are selling products to other businesses, while B2C companies are selling products directly to customers. An example of a cleantech company that is B2B is a company making anodes for lithium ion batteries for use in grid scale applications. In this case the customer would be a battery maker who would incorporate the product into their device, and the end user may be a utility of residential households. An example of a cleantech company that is B2C is a company developing solar powered plant watering systems for residential households whose end-user is also the customer: the individual house owner.

This is an important distinction as the approach of the companies is necessarily different if their customer/user is a business or an individual consumer. Literature on UCD is generally geared toward B2C companies, and the B2B case can be trickier for the designer as the end-user and customer (or buyer) are sometimes not the same and have different wants and needs for the product. [65] This is echoed by one founder from Company 10 who said, "if you're going B2B, you have to keep in mind that the guy you're talking to is not necessarily the guy who's going to make the purchase. That's what is kind of tricky commercially speaking."

In the interview study done herein, 73 percent of companies interviewed are B2B and 27 percent B2C. When asking questions about gathering preferences from users/customers these need to be defined in a way consistent for both B2B and B2C companies. I focus in this work on customer preferences, which although not always end user preferences, are the main focus of many startups as they are the ones who will buy the product. With this distinction in mind, I analyze quantitatively and qualitatively customer-startup interactions through a series of interview questions.

4.3.2 Customer Relationships: Quantitative Analysis

For the interview study, I formulated questions relevant to determining how each company's relationship with customers informed the PD process. These questions were outlined in Chapter 2. I find 83 percent answered that they would characterize their product as "user-centered" and 91 percent said they talked with customers before starting design, see Figure 4-1. Also, 22 of the companies said their main competitive strategy was customer focus over cost reduction or technology focus. I also determined when the companies first talked to customers with respect to their incorporation date and concept generation/ideation. I further find 73 percent of the companies gathered user preferences by interviewing single potential users, and the rest use other methods such as focus groups, written surveys, industry consultants, conferences, social networks, etc. This method of gathering user preferences is in line with UCD techniques which emphasize face-to-face conversations with potential customers. These results demonstrate that these hardware startups are aware of the importance of customer interaction.

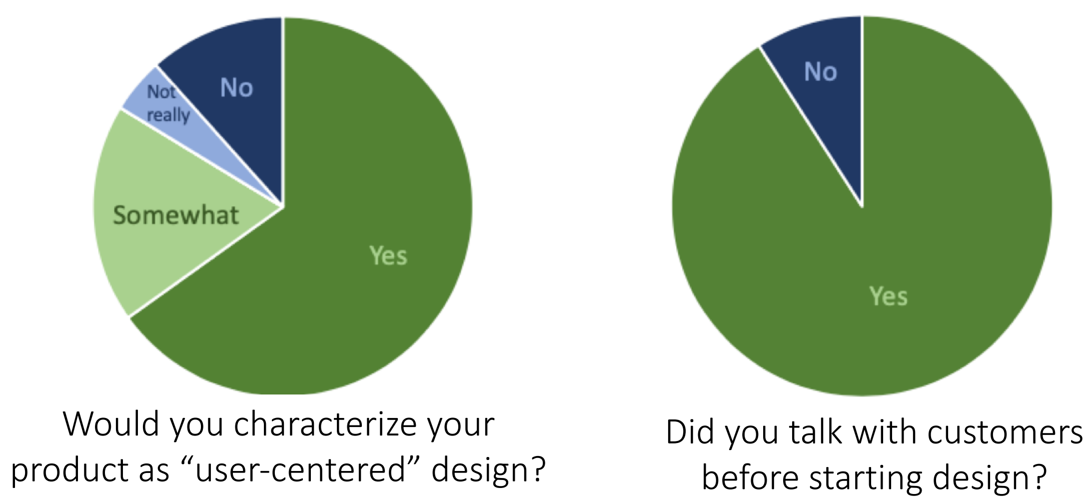


Figure 4-1: Customer Relationships of Interviewed companies

Left: Whether companies consider their product user-centered design. Right: Whether companies talked with customers before starting design.

Despite the majority of companies embracing UCD, there are still companies that wished in hindsight they had talked to customers earlier or talked to more customers. For example in Figure 4-3, this company was prototyping for over four years before first approaching customers. I explore more of these examples in the next section.

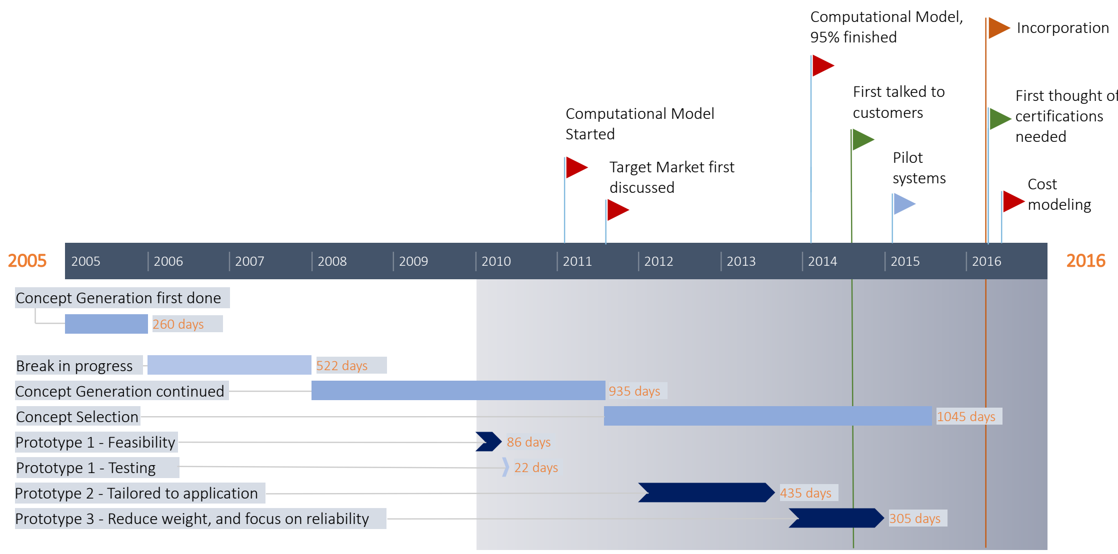


Figure 4-3: Company Timeline Example of Talking to Customers Late

Timeline of a company that waited until their third prototype (4 years) to first talk with customers.

4.3.3 Customer Relationships: Qualitative Analysis

The majority of the quantitative data from above points to companies understanding and appreciating how important customer relationships are at least when answering survey type questions. However, I find there is actually a large range of views about the importance of customer input during PD within the companies. Some companies are very serious about involving customers from the very beginning, doing iterative customer testing during PD, and taking customer feedback into direct consideration during the next prototype. In contrast, there are some companies that are skeptical of the ability of customers to give useful and informative feedback to inform PD. For example, in the interview with Company 13, a B2B company:

EL: "How important do you find gathering user preferences?"

C.13 CEO: "Not particularly important because they're not in a position to know what's possible. They're not educated in the technology. So they would tell us 'We're happy enough with what there is' until we tell them they could have something better."

This company hired industry consultants to informally gather customer preferences, and as is apparent above, they are not convinced the customer and eventual end user's ideas are helpful for design. On the other end of the spectrum we have Company 19, also a B2B company that realized the importance of customer input during PD:

EL: "What would you say your competitive strategy is? Please choose from: technology leadership, cost leadership, customer focus, or other."

C.19 CEO: "So, I'm inclined to say the customer focus is really important because whoever needs the battery, it must be customized to the applications that they have in the end. Although it wasn't important to us in the beginning, we realized that to sell our product [it is important]. In terms of hours, we spend a lot of time understanding what our customers exactly want and then design batteries that give them what they want. Not because we like to do that, but we need to do it."

A good summary of this tension between taking all customer feedback seriously or with skepticism is given by the CEO of Company 12, a B2C company:

EL: "How important do you find gathering user preferences?"

C.12 CEO: "The tricky part is believing everything that you hear. Because, probably, you shouldn't believe everything you hear, but on the other end, you shouldn't dismiss things that you didn't want to hear."

This tension means customers can be brought into PD too late. For example, Company 5's CEO lamented not having gathered enough customer feedback early enough:

> **C. 5:** "If I were to do it differently, I would've had a better understanding. Talked to a lot more people and understood the real scope of all the decisions I'm making rather than my perceived scope of those decisions."

However, one interviewee gave an example of how customers can also cause slowdowns in PD through feature creep (discussed in the previous chapter). When discussing what he sees as the differences between user preferences and design requirements he said:

> **C. 11:** "Yeah, inevitably, those conversations [with users] can end up being combinations of those, so it's important to avoid preferences, because that's not so critical up front. The must haves of the product, which I would say are not preferences, they're requirement specs, that would be... critical, but the user preferences, being non-critical features that sound interesting, and I get hung up on. You want to try to cull those conversations, so those can be red herrings."

Two conclusions are drawn from these quantitative and qualitative analyses. I find customers need to be a part of PD from the very beginning. This has long been known by the community, and most startups seem to be aware of this and implementing UCD as seen in Figure 4-1. It is concluded by literature and the majority of companies interviewed, that it is best practice to engage with customers as design begins or even before. I also find that customer feedback must be filtered appropriately for validity as customers are not always aware of what is possible or what they really want. From this analysis it is not yet clear how to best use and evaluate customer feedback, and further research is needed to understand ways to filter customer feedback.

4.3.4 Customer Relational Requirements

I conclude from the literature and above analysis that customer relationships are critical for PD success, but customer preferences and feedback must be tested for efficacy just like products must be. I suggest adding customer relational requirements to technical requirements of products as a strategy to accelerate PD. I give examples of customer relational requirements in Appendix D.

4.4 Investors

All startups agree on the importance of investors because without money, a startup cannot survive. Furthermore, it is known that investors can bring more than money to the startups. Kollman et. al. found there is a lack of research on startup-investor relationships despite the fact that initial investors often help with devising successful strategies for future investment rounds which is useful for any startup in any sector [82]. Much of the available literature on investor relationships with companies focuses on the formalized and somewhat anonymous communicative relationship between investors and companies [82].

It is clear that finding the right investors is crucial to success, but less clear how to accomplish this. I examine the relational requirements for investors through the lens of (1) pressure exerted by investors on companies and (2) investors as sources of information rather than just money.

For the companies interviewed, Figure 4-5 shows the types of funding and investor relationships they have or have had. In this figure, companies can have several sources of funding.

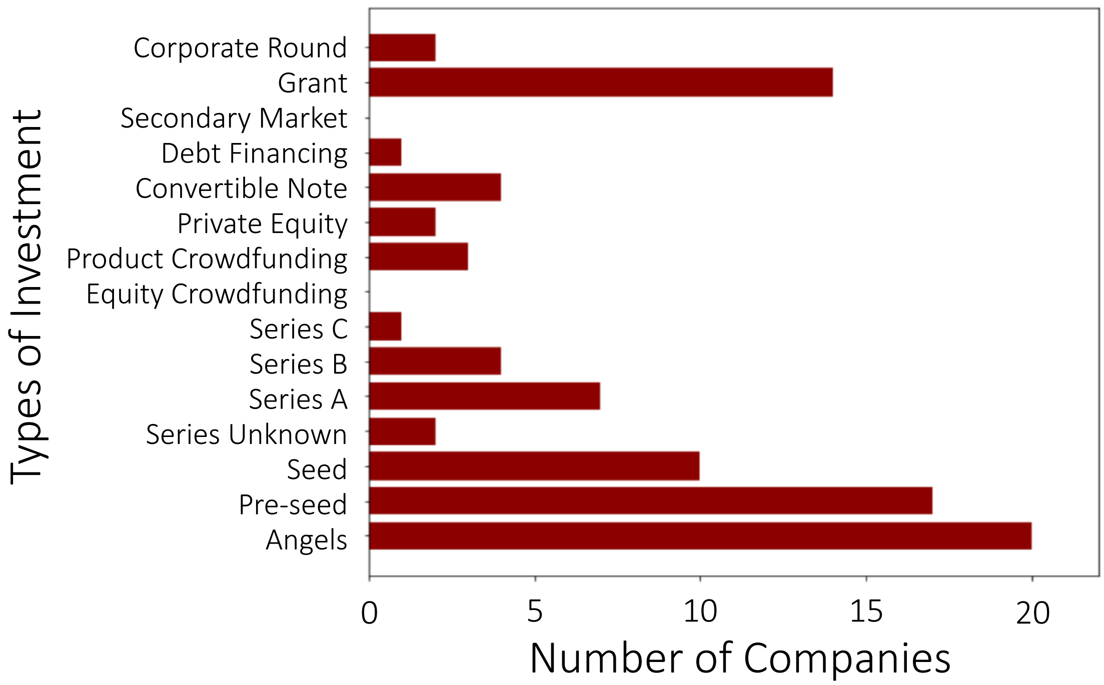


Figure 4-5: Types of Investment

Types of investment the interviewed companies have had or do have. N = 38

As can be seen in Figure 4-5, the major investment groups for the companies are angel investors, pre-seed and seed investors, and grant funding with 10 or more companies. Therefore the following analysis applies directly to these types of relationships, although generalizations to other funding types can be made.

4.4.1 Pressure by Investors

One of the main motivations for this research is mismatch between product development timelines in cleantech and investor expectations To investigate how this manifests at the level of startups, I asked the interviewees:
"Has your company been pressured by funding sources to speed up design due to slow development timelines or short investor timelines?"
A: No, they give us all the time we need, B: Not really, we don't feel pressured to rush, C: Somewhat, D: Yes, but not unreasonably, E: Yes all the time
As can be seen in Figure 4-7, I find 56% of interviewees answered yes in some form, and 37 % answered no in some form, with 7% saying sometimes.

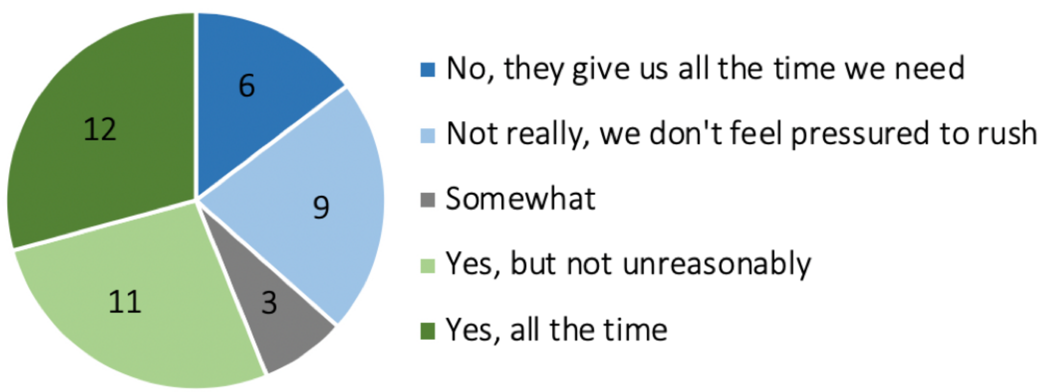


Figure 4-7: Pressure by Investors

Interviewee response to how pressured they feel by investors to accelerate PD.

These numbers suggest a majority of companies are still pressured to speed up at some point in their PD, as was one of the main assumptions of this research. However, over 40% of respondents are not rushed by investors. This could mean that after Cleantech 1.0, investors in Cleantech are taking a more patient approach to PD for this sector, allowing for longer runways before return on investment. Another reason for this could be that investors do not feel it is their job to handhold the companies in their portfolio, and that it is up to them to produce in a timely manner or not. Then, if they do not meet the milestones as agreed upon, the investor could pull out of the venture.

In summary, these numbers show that active pressure from investors should be expected but is not guaranteed. It is also not clear whether the addition of pressure or lack of pressure by investors has the better outcome in actually speeding up cycles of learning as is seen in Figure 4-9. I find little difference in the amount of time it takes companies to prototype whether investors pressure them or not.

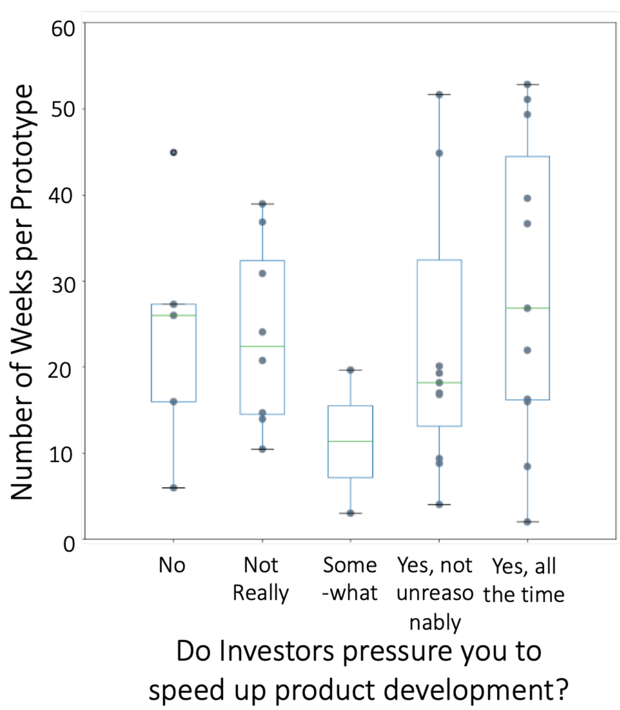


Figure 4-9: Pressure by Investors vs. Number of Weeks per Prototype

Interviewee response to how pressured they feel by investors to accelerate PD.

Pressure by investors toward startups can also be viewed as a lack of communication between the investors and startups. In 2017, Zelkova Ventures, a venture capital (VC) firm did a survey of investor-startup relationships finding that while over 75% of founders think they have kept their investors up to date, only 58% of investors think that [91]. This indicates a fundamental mismatch in communication expectations between investors and companies that could contribute to a lack of trust.
An example of this comes from an interview:

> **EL:** "Have you guys been pressured by funding sources for being slow in iterating or anything yet, or has that not been a problem?"
>
> **Comp 45 Rep:** "No, and I think the key is communication."
>
> **EL:** "Just honesty?"
>
> **Comp 45 Rep:** "Yeah, we're very transparent about our product. They got all the issues we encounter, especially once we acquire a source of funding, they get sort of like, yeah, you get invested, so you're on our team, now. Not to say that we were lying before getting them on the team, but there [were] no hidden standards or anything, we're very transparent about our stage. Maybe they did not realize the time to market side of things. But I was always completely honest about that aspect."
>
> **EL:** "Yeah."
>
> **Comp 45 Rep:** "And I feel like communication is really critical in making them feel involved, as well, in the whole process. They don't get frustrated if they feel like they're part of that."

From this analysis, I find pressure by investors potentially caused by a lack of trust does not necessarily push startups to perform faster. It is suggested that matched communication expectations and clear flow of information between the two parties would help overcome this lack of trust.

4.4.2 Investors as Sources of Intelligence

In their work, Zelkova Ventures also found that only two thirds of startups think their investors understand their specific business [91]. This leaves a third or more of startups that do not trust their investors to help in any way but with funding. These are what could be called "dumb money" sources as opposed to "smart money" which the *Financial Times* describes as: "sophisticated investors who tend to pick the right moment to buy or sell assets because they can identify trends and opportunities before others do." [96] Companies prosper when they find investors that can help with thought leadership, attracting other investors and stakeholders, knowing the market fit, and business dealings.

There are several examples of companies within the interviews receiving useful information and advice from investors that ultimately sped up their PD process. One company got advice, although no money from a potential investor that helped them accelerate their PD in this example:

> **EL:** "In hindsight, would you have thought of manufacturing earlier in the design process?"
>
> **C.25:** "We originally planned to and I'm very glad we did. So I wouldn't say, well just started working on it earlier, we did start on it way earlier than we planned. It was good."
>
> **EL:** "Why did you do that?"
>
> **C.25:** "Feedback from a potential investor."

> **EL:** "Well done investor."
>
> **C.25:** "Yeah. And we really liked them. They've never given us money, maybe one day. You know, they give you lots of ways to add value."

Another example of an investor playing a larger role is shown here with the investor helping to set the company direction:

> **C.43:** So actually one of the investors was involved at that point [very beginning] since we didn't have a CEO at that point. So he was periodically involved [in development]. I'm sure he was always thinking about "okay, how am I going to make money off of this thing?"

As demonstrated in these examples, looking for investors to provide vital intelligence and be "a part of the team" could help accelerate PD in various ways including helping with PD steps, finding more investment, or advising about market strategy.

4.4.3 Investor as Customer

One model that several of the interviewed startups use is the investor-as-customer model. This is useful for early stage startups to not have to maintain separate customer and investor relationships as well as having clearly defined communication lines and expectations. For example:

> **C.22 Rep:** I mean the first customers- let's see we were funded on our research program from the [redacted]. So, we designed to the specifications of this program so that the customer was the program manager.

As with this company, many government grant funded startups have this type of model which accounts for 15 of the 55 companies interviewed. Other companies can find this type of model as well with investment from large corporations.

4.4.4 Investor Relational Requirements

I conclude from the above analysis that investor relationships are important for PD success, but are often not utilized to their fullest extent by startups. I suggest adding investor relational requirements to technical requirements of products as a strategy to accelerate PD. While these investor relational requirements are not new ideas, for startups scrambling to get everything done, adding specific investor relationship requirements could be the difference between cultivating trusted investors that push PD forward, and those that add stress to the company. I give examples of investor relational requirements in Appendix D.

4.5 Manufacturers

The last relationship I found to be critical to PD is that with manufacturers. In literature, there are design strategies that were developed to help overcome the difficultly of making a cost-effective manufacturable product. Two specific methodologies are Design for Manufacturing (DFM) and Design for Assembly (DFA). Both started in the 1960s, and were brought into common use in the 1980's. They are widely in use by established companies and often combined to be called DFMA. These design practices are often discussed today under the term "concurrent engineering" or "integrated product development" in which there is a parallelization of PD tasks including design engineering, manufacturing process design, and market development.

For startups, this concurrent engineering style presents a greater challenge due to the smaller teams that usually lack manufacturing or assembly expertise. This makes relationships with manufacturers paramount for startup success. I examine the relational requirements for manufacturers through (1) the answers to the manufacturing questions in the interview about when companies first thought of manufacturing and their use of DFM, and (2) qualitative perceptions on if they should have involved manufacturers in their process earlier.

4.5.1 Manufacturing Relationships: Quantitative Analysis

In Figure 4-11 I find two-thirds of all the companies claimed to be using DFM and 80% used at least some DFM principles. This indicates that by the time of the interview the startups were aware of the importance of DFM for PD success.

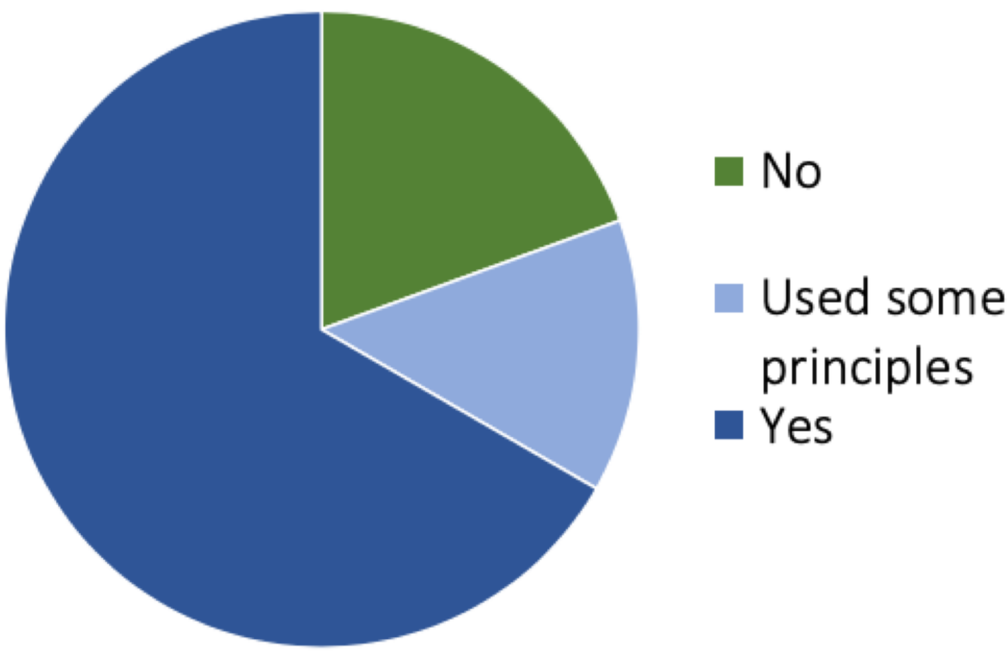


Figure 4-11: Design For Manufacturing

Answers to the question: Did your company use DFM during product development?

I then look at when the company first discussed manufacturing in the weeks before and after beginning their first prototype. This is plotted versus how long the prototyping took in weeks on average for that company in Figure 4-13. I find that 70% of companies do not think about manufacturing until after their first prototype is finished, and 38 % until after their 2nd or 3rd prototypes are finished. This indicates that while DFM is acknowledged as important by most of these startups, many do not bring in these principles until later in PD. The median time after prototyping begins when manufacturing is first discussed is 20 weeks. Also in this figure are highlighted companies which explicitly mentioned without prompting that they wished they had talked about and/or implemented DFM principles earlier in PD. Over 15% of companies brought up this failure mode unprompted. I also find no correlation between when they first discussed manufacturing and average time per prototype. One hypothesis for this result is that not thinking about manufacturing does not slow down individual prototypes, but rather makes it necessary to do a large number of prototype sequences in total before the product is ready for market, therefore lengthening PD.

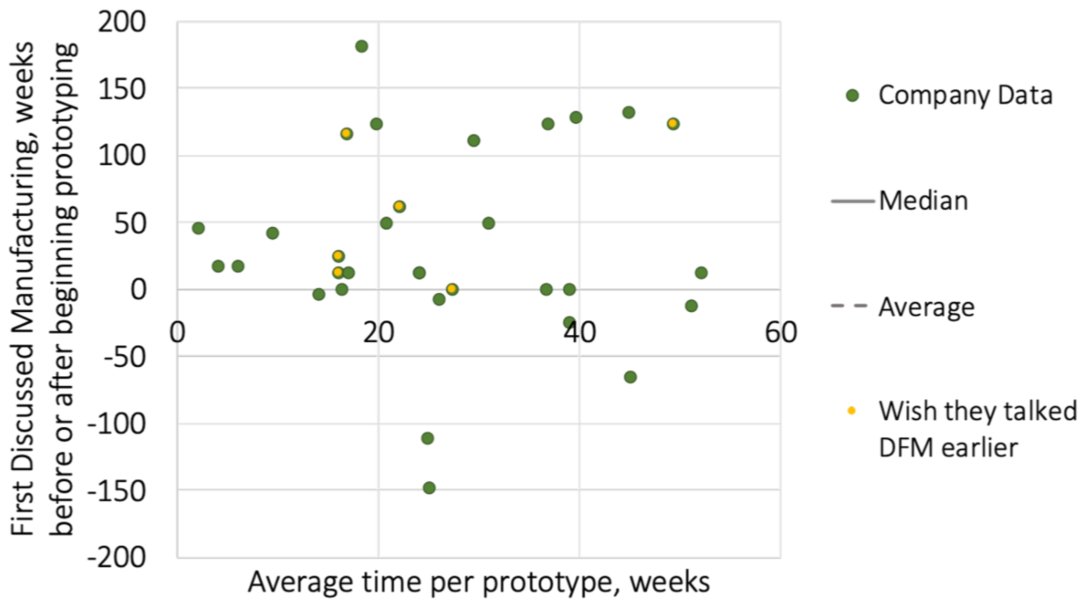


Figure 4-13: First Discussed DFM vs. Average Time per Prototype

When companies first discussed manufacturing in weeks before or after beginning their first prototype plotted versus the time it took them to complete each prototype on average in weeks.

I further analyze manufacturer relationships through qualitative analysis of the interview transcripts.

4.5.2 Manufacturing Relationships: Qualitative Analysis

With customer and investor relationships there was tension between trusting their input and being skeptical of their ability to understand the product or market as well as the startup itself. This is very different with manufacturers in which no tension in views is found in the interviews. Companies uniformly believe manufacturer input is useful and important. This makes sense because the expertise balance is weighted toward the manufacturer not the startup.

Neglecting this relationship with manufacturers can cause slowdowns in PD. For example, one company averaging a prototyping time of about 3 months for the first 5 prototypes, took 12 months to finish prototype 6. When asked what they would do in hindsight for this prototype they responded:

> **EL:** "For this [prototype], in hindsight would you do anything differently?"
>
> **C. 28 CEO:** "Yeah we should have brought our contract manufacturer in to the design process. I think we could have done more DFM sooner and also like design for assembly. We did not think about it until it was too late."

Company 28's timeline is shown in Figure 4-15.

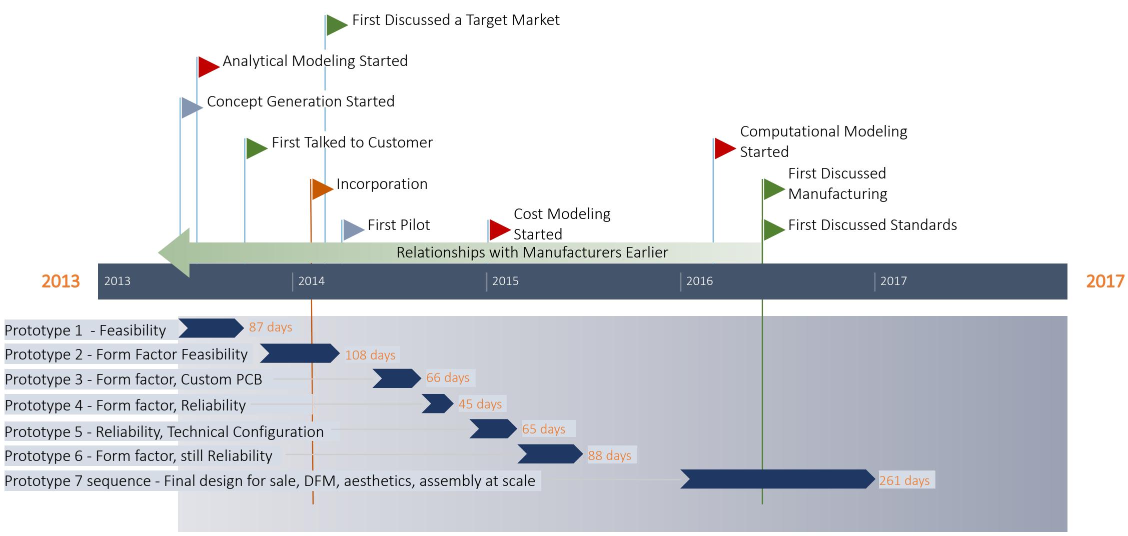


Figure 4-15: Company Timeline Example of Discussing Manufacturing

Timeline for company 28 showing the point at which they first discussed manufacturing during prototype 7.

Another example comes from Company 4:

C. 4 CEO: "So maybe if we had known a little bit more about that earlier, we would have designed for ease of manufacturing to begin with, as opposed to the other way round, where we designed, then turn to manufacturer realize it wasn't feasible. But you know that we had too many things that would have needed to be tooled and yes. So in hindsight, having had knowledge of manufacturing processes earlier on and the same process, could have saved us time and money."

Company 4's timeline is shown in Figure 4-17.

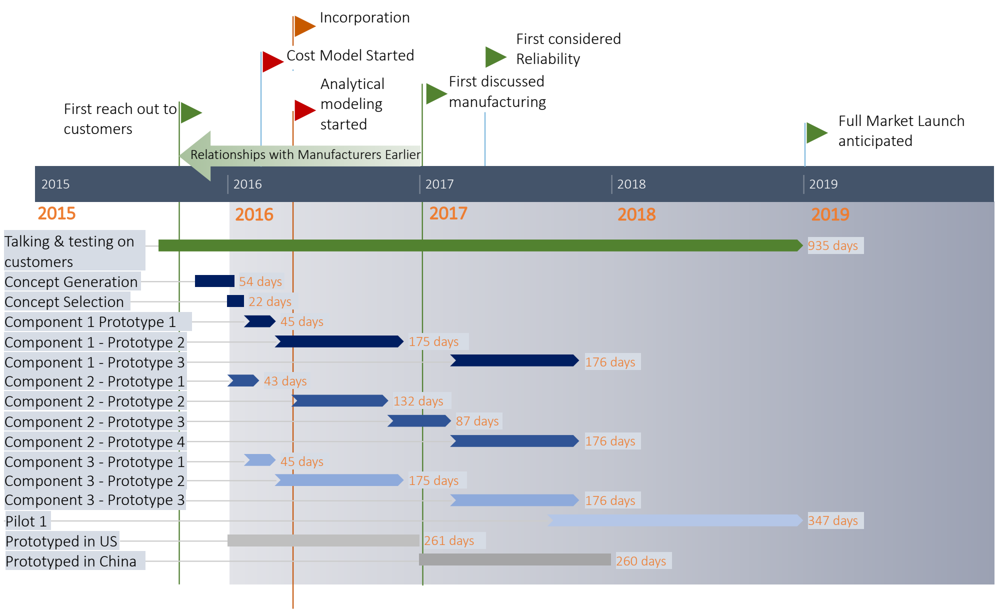


Figure 4-17: Company Timeline Example of Discussing Manufacturing

Timeline for company 4 showing the point at which they first discussed manufacturing during prototype 3.

This example demonstrates the direct link between DFM and accelerating PD as without working with DFM or manufacturers the product designed can often not be manufactured in its current form. One interviewee offered up a post mortem of the company's early approach to DFM and relationships with manufacturers (before the interviewee was brought in to the company a few years in, as a very experienced CEO, to save the company):

> **CEO:** "So they had this kind of very academic idea of contract manufacturing that didn't turn over and we were like, we're going to hire someone that we have a history with that is very nimble and resourceful, and we're going to put our people in there and figure it out with them, because we don't know enough to tell them what the right steps are and the documentation and the procedure. So they were very misguided about manufacturing as a whole. The reason I said all that was, I would not use the word for design for manufacturability because they would completely misunderstand what that means. They would think that means they need to design it and then tell someone how to manufacture it... [They did not understand that] We need to have an engineer in the manufacturer from day one."

This is a candid assessment of how engineering students can come out of their education without a good understanding of what type of relational requirements are necessary for efficient PD. Rather than DFM being understood as having a manufacturer as part of development from day one, the engineers thought it meant designing something that could theoretically be manufactured and then taking it to a manufacturer with their requirements.

There was further evidence of the need for this direct relationship with manufacturers as companies explained that close physical proximity to manufacturers immediately accelerated their PD. For example, several of the start-ups interviewed directly mentioned that when they moved to China, where their manufacturers were located, their PD would accelerate and market readiness became a reality.

> **EEL:** "Which steps of the list that we've gone through, do you think slowed you down the most? And which do you think can be made the fastest? Pick any that you think."
>
> **C.4 CEO:** "So I mean we definitely did notice how like we were prototyping in the U.S. for most of 2016, and then 2017 went to China, right. And it did help us so much. I remember like spending... we spent so much time looking here for people that could do [process X]. And, that's what took forever. So I agree, quoting one of our investors, like prototyping in China just like speeds you up so much."

In Figure 4-19, it can be seen that the majority of companies I talked to were incorporated in the US, but many of those companies manufacture in China.

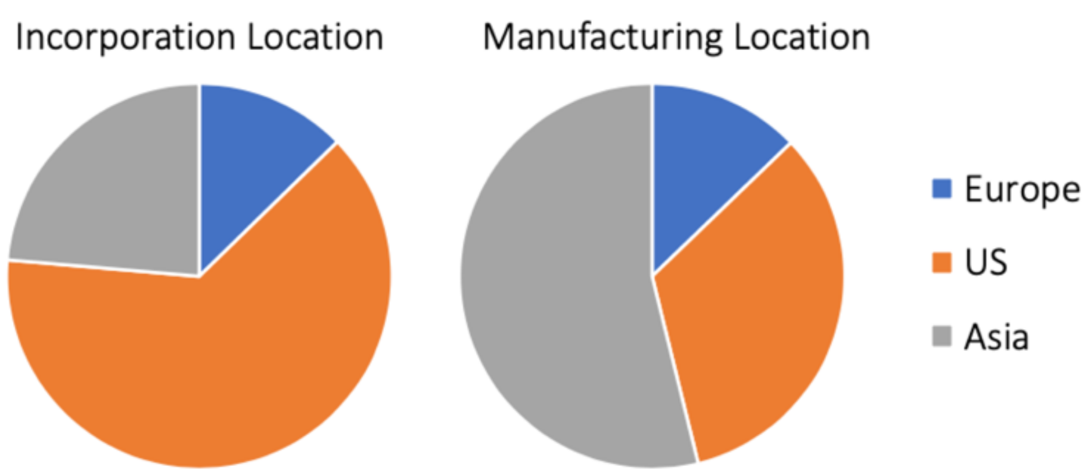


Figure 4-19: Locations of Incorporation and Manufacturing

Over 60 % of companies interviewed are incorporated in the US with around 23 % in Asia, of which over 50% manufacture in Asia.

One hardware accelerator, Hax, has even made it their model to move startup companies to China to be right next to their manufacturers as a way to accelerate PD. I find many companies incorporate in the US and manufacture in China and therefore extra care must be taken to develop these manufacturing relationships that are located far away. This should be considered when first choosing manufacturing partners.

I conclude from the above analysis that manufacturer relationships are critical for PD success, but are often neglected until too late in the process. I suggest manufacturer relational requirements be added to technical requirements of products as a strategy to accelerate PD. These requirements may help startups avoid many of the pitfalls the interviewees fell into when forced to completely redesign after their product was found to be not manufacturable at cost. I give examples of manufacturing relational requirements in Appendix D.

4.6 Conclusions

Following the technical strategies outlined in Chapter 3, in this chapter I have focused on an operational strategy: the inclusion of relational requirements during PD. I outlined the importance of relational requirements with customers, investors, and manufacturers for the success of hardware startups. I propose the operational strategy of codifying relational requirements alongside technical requirements during requirement definition as a PD acceleration tool. The findings in this chapter are summarized here:

I find that the customer needs to be a part of PD from the very beginning as has been shown before in literature. Over 83% of the interviewed companies say they use UCD, and 91% say they talked with customers before starting design. However, there were exceptions including one company who waited over four years to first talk with a potential customer. I also find that customer feedback must be filtered appropriately for validity as customers are not always aware of what is possible or what they really want potentially causing feature creep and other inefficiencies. This is an area for future research.

Regarding investor relationships, I find the majority of companies in this study have angel, pre-seed, seed, and grant funding. I find 40% of companies do not feel pressured to accelerate PD by investors, while 56% do feel pressured. This indicates there is active pressure by investors to accelerate PD should be expected, but is not guaranteed. I also find there is no correlation between feeling pressured to speed up and the actual time to prototype for startups. Furthermore, I find pressure by investors potentially caused by a lack of trust does not necessarily push startups to perform faster. I conclude that matching communication expectations could enable a clear flow of information between the two parties and overcome this lack of trust. Lastly, I find using investors as a source of information as well as money can be beneficial to PD as well as trying the investor-as-customer model enabled by grants.

The third relationship explored is with manufacturers. I find over 66% of interviewed companies claimed to used DFM, and over 80% used some principles. Through qualitative analysis I find neglecting manufacturing relationships that foster DFM can slow down PD. However, when analyzing the timelines, I find the median time after prototyping begins when manufacturing is first discussed is 20 weeks, and over 70% of companies do not think about manufacturing until after their first prototype is finished. This indicates that while companies know about how important manufacturing and DFM is, they often think about it too late in the process. Lastly, I find being in close physical proximity to the manufacturer can accelerate PD.

In the next chapter, I present several technological strategies for accelerating product development using tools such as high performance computing, machine learning algorithms, and generative modeling.

Then in the following chapters I present a tool I developed using some of these techniques.

Chapter 5

Interview Analysis III: Tools for Accelerated Design, Build, and Test

In the previous two chapters I presented a set of acceleration strategies formed from quantitative and qualitative analysis of interviews with hardware startup practitioners. These are a set of technological and operational strategies that could expedite PD timelines.

In this chapter, I present an outlook for technical acceleration strategies that are cutting edge and have only started to be used by startups. I expand the list of strategies from previous chapters to include tools like automation, machine learning (ML), high performance computing (HPC), 3D printing, and more. Such strategies are not yet broadly employed within industry, especially in early stage startups, and companies that can capitalize on them will have a competitive advantage. Cleantech hardware companies with the challenges inherent in this sector could employ such strategies to accelerate PD and become more viable.

A vision of accelerated systems development can be visualized as seen below in Figure

5-1. [1]

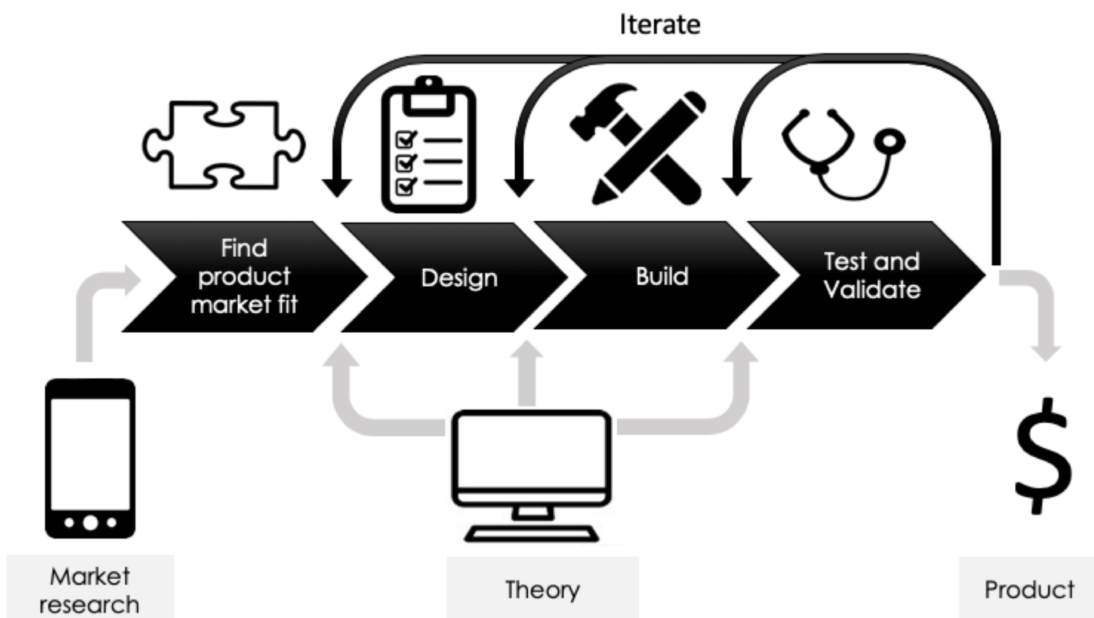


Figure 5-1: Accelerated Systems Development

This simplified schematic shows the three steps of systems development covered in this chapter: designing, building, and testing all informed by theory. Also the previous steps of market research and finding product market fit are also shown as discussed in previous chapters.

In the following sections, I will go through the design, build, and test parts of this process. I analyze what the interviews have taught as well as introduce state-of-the-art strategies that could help product development in the future. I will then briefly introduce a new technical testing acceleration method I developed for use in the Cleantech sector of solar photovoltaics.

[1]In this section I call the product a "system" to denote the emphasis on technical considerations of the product.

5.1 Design

5.1.1 Status Quo

In the interview, the section on concept generation and selection shed some light on the process these companies used to design their product. One finding showed that 35% of companies interviewed think designs were killed off too quickly, and 58% of interviewees thought designs were pursued too long. This demonstrates some dissatisfaction with the ability of the teams to explore all the concepts they wanted to and even more dissatisfaction in deciding when to move on from a concept.

Another finding is that the ways concepts are chosen varies greatly between companies. As seen in the Figure 5-3, prototype and test is the most common way a concept is chosen, with voting and pros/cons being second most used.

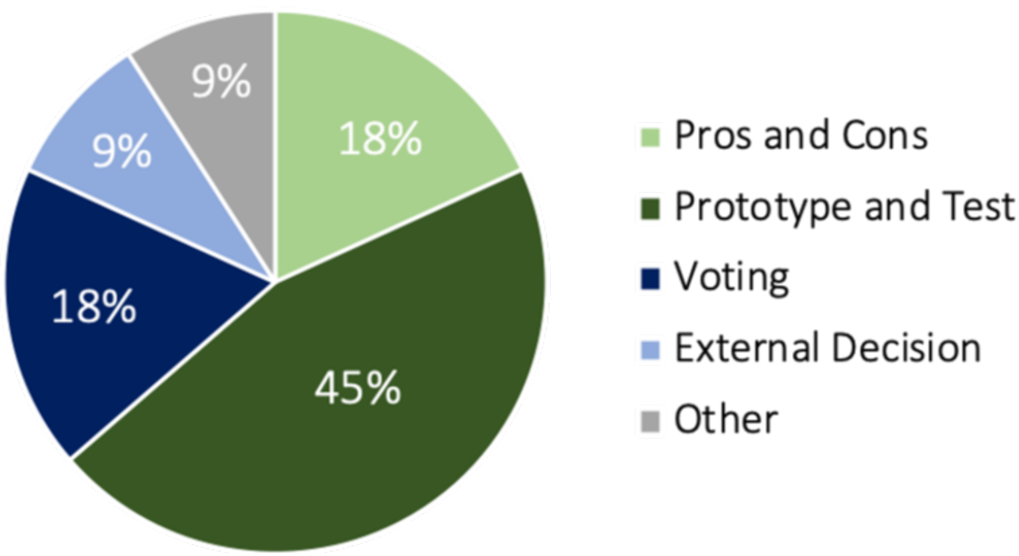


Figure 5-3: Concept Selection Methods

Concept selection methods of the companies, N = 31.

While the "prototype and test" method of selection is rigorous, it is not a selection method that allows for a large number of concepts to be considered. The concepts that are prototyped have, at that point, already been selected through another method. Also, rarely is more than one concept prototyped extensively. Rather, companies move forward relying on rudimentary modeling, intuition, experience, and ultimately team voting or consensus to choose what to prototype in the first place. This style of concept selection can prove to be a failure mode, limiting the design parameter space as is explained in the interview with Company 19:

> **Company 19:** "I think the biggest mistake or like one of the problems was that in the beginning, like we sat down to figure this out for two days and then we kind of had an idea and then we just stuck with it."
>
> **EL:** "So you didn't do the thing where you make a bunch of concepts and then try to winnow them down."
>
> **Company 19:** "Exactly. So that is what we're trying to do now. But we didn't do that in the beginning and I think that was really clearly a mistake... I think the specific mistake that we did is that we thought we can know which one was the right one as scientists. We [thought we] knew what the best one was."

In this quote, the company representative discusses the mistake of simply choosing the first seemingly viable concept which was ultimately not the right one.
This sentiment was echoed by several companies. For example Company 9, in hindsight, wanted to explore more of the design space up front:

> **Company 9:** "I think we could have been more imaginative, so we could have explored other options too, but maybe we spent very little time, so

> at the end we got something of ... a good design, but still we could have done better."

These examples demonstrate the call to both explore the entire parameter space and to down-select concepts to prototype. Within academia and industry, tools to help with these two steps have been developed and studied for decades. With the advent of great computational power and open source software, these tools are now more available to startups. In the next section I highlight some of these cutting edge technical tools that startups could use to explore design parameter space and down select a concept.

5.1.2 Strategies and Tools for Future Design

System design has been widely studied including ways of making designers more effective with computational tools. In 2015 Bernal *et al.* gave a comprehensive overview of some of these techniques [10]. The explicit goal of these computational tools is to explore as much of the design space as possible so as to find the optimal solution, evaluate those solutions virtually without physically building anything, and select one (or a few) to build.

Computational tools to assist with design generation and selection have been used for decades. One example is computational parametric modeling which can organize geometric relationships of a system in a hierarchical binary tree structure updating automatically with part visualization as the design changes parameter values [75]. Expert systems are another example that have already been in practice for many years in which a set of libraries containing expert knowledge are used to emulate human decision making based on rules [146][34]. Another strategy called *case-based reasoning* searches for previous solutions to similar problems through a set of constraints ordered by importance and adapts those solutions accordingly [83]. One major problem with both *expert systems* and *case-based reasoning* is that the answers are limited to already known solutions or experiences[98][97]. Many of these approaches can therefore over-constrain the design process.

One computational tool that overcomes many of the problems with these previous computational tools is called *generative design*. This method quickly explores permutations of a system given input constraints such as materials, manufacturing methods, cost, and spatial requirements. Then each generated design is tested virtually with the input constraints and the model learns from the successes and failures of that design. There are many generative design systems in literature for generalized design as well as specific applications including *Fusion 360* [47], *Dream Lens* [101], *DreamSketch* [77], *GEM-NI and MACE* [169][168], *DesignN* [81],*GenYacht* [80],*Genoform* [84], *ParaGen* [152], *Dexen* [70], *GENE_ARCH* [22], and more. [119][164][3] There have also been initial successes with several generative design tools finding a solution with equal or better performance for less cost. [148]

Some generative design abilities have been integrated into CAD platforms such as AutoDesk Fusion 360 which can generate hundreds to thousands of designs almost instantaneously. [47] This accessibility makes these techniques useful even to early stage hardware startups for PD acceleration. Figure 5-5 depicts a visual created by Autodesk for how their generative modeling software can accelerate PD as well as generate more optimal designs with more of the design space explored.

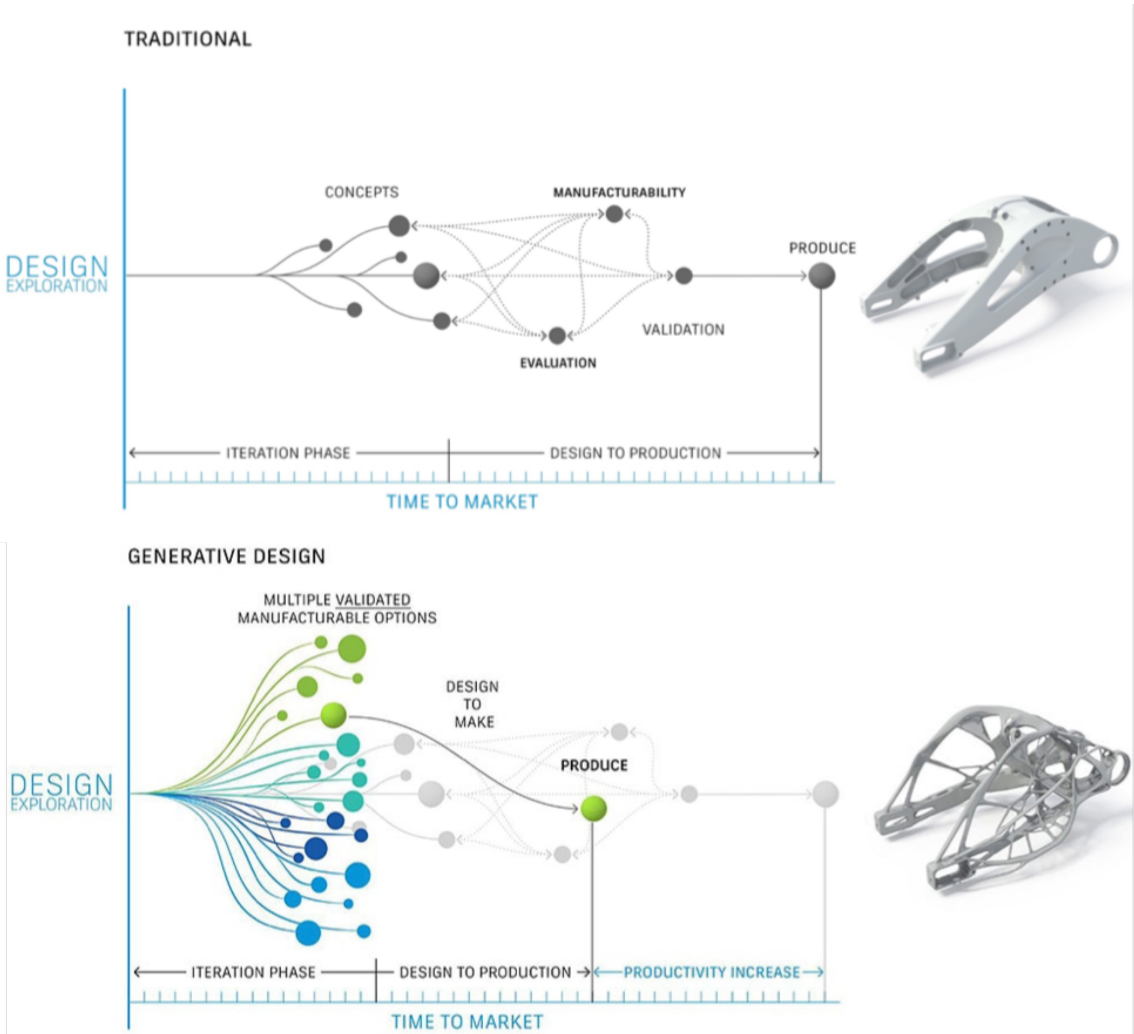


Figure 5-5: Generative Modeling Examples from Autodesk

Top: the traditional approach to design with 1 to 3 options considered, one chosen, evaluated, validated,and finally produced. Bottom: New generative model-based design with dozens of already validated options considered, and one produced causing a significant productivity increase.

So far I have discussed mostly mechanical, thermal, or optical design, but there are also computational tools to assist with electronic design. Machine learning based models for electronics design, virtual build, and testing have also been growing in use.

Just as one example, the NSF founded a cooperative Industry/University research center in 2018 called the *Center for Advanced Electronics Through Machine Learning* whose mission is enabling "fast, accurate design and verification of microelectronic circuits and systems by creating ML algorithms to derive models used for electronic design automation." [21] With nine industry and three founding university partners, this center publishes research on ML-based electronic system development including design space exploration with neural networks, ML based design for security of IoT system, recurrent neural network models for simulated circuit aging, etc. This is just one research repository of work transforming how quickly electronic equipment can be optimally designed, built, and tested.
Examples including expert systems, case-based reasoning, generative modeling, other machine learning assisted design tools, and CAD visualization are enabling designers to explore more of the design space and down select concepts to build faster. In the next section I explore tools also making physical building more efficient.

5.2 Build

Computational models have increased the efficiency of concept generation and selection, making the building of physical prototypes less necessary if a virtual model is powerful enough to validate the design. [17] This makes the design and build steps less distinguishable. Therefore the models presented in the design section can also be thought of as build tools in a virtual environment. This is especially true if the interface with the software renders a visual prototype that can be tested with mechanical, thermal, and other physical constraints through CAD and finite element modeling. These virtual builds allow for parallelized testing of larger numbers of prototypes than possible if prototyping physically. However, once they have been validated virtually, physical prototyping is the essential next step.

5.2.1 3D printing

A set of tools have been adopted in the past few decades for accelerating physical prototyping as well. The most common of these, especially for hardware startups, are 3D-printers whose price has fallen and quality risen to the point of being broadly applicable [163]. A study done in 2018 tracked patents of incumbent and new firms that used 3D printing. In this study it was found that incumbent firms adopted 3D printing first and have always had more patents coming from the use of 3D-printers. However, new firms like startups have also begun to adopt 3D printing in the past decade for use in product development [24].

During the interview, 11 of the 55 companies mentioned 3D printing as an essential step in their prototyping without any prompting. (No questions were asked about 3D printing.) One company explicitly mentioned how 3D printing has enabled them to accelerate prototyping:

> **Company 14:** "We leverage a lot of 3D printing to minimize the tooling cost and complexity."
>
> **EL:** "Are you satisfied with how fast it was made?"
>
> **Company 14:** "Yeah, so again the use of 3D printing is very helpful. We iterate very quickly."

There were two complaints raised by interviewees about 3D printing as prototyping tools. One was that the quality of parts from these printers can be very low, so to get adequate parts for prototyping, it may be necessary to invest in expensive top-of-the-line 3D printers. Another complaint was that while 3D printing early prototypes can be helpful, if DFM is not accounted for, these parts cannot actually be manufactured. For example, one company explained:

> **EL:** "So you got that 3D printed, but how do you do it with the injection molding?"
>
> **Company 10:** "The nozzle had loads of problems... because the plastic is not cooling the same way... this kind of stuff you don't know when you're used to designing with a 3D printer."
>
> **Company 10:** "Yeah, When you're designing... it's like 'this part is weak'. So I'm going to put a ton of material [so it] is going to be more robust. And, then when you get injection molding, when you get to these DFM issues, just like okay, now I have to change completely the design of my part."

To overcome these issues, one company worked toward a rapid prototyping solution that took manufacturing into account:

> **Company 27:** "I had this kind of tabletop, injection molding, like set up and-"
>
> **EL:** "Like a hopper?"
>
> **Company 27:** "Yes. Actually, ketchup dispensing guns and it was this whole prototyping process that gave me almost the same results as a manufacturer part, but we could go from concept to CAD and 3D print tests and then going back to CAD on a three to four day cadence from prototype to prototype."

These examples demonstrate the acceleration opportunities brought about by 3D printing while also pointing to the growth areas for 3D printing technology including part reliability and manufacturing capability.

5.2.2 Automation

Further acceleration of physical prototype builds can come through robotic and automation approaches. One example where this works well is PCB design and fabrication which has been greatly accelerated using pick and place machines. These machines can go from virtual design to fully assembled PCB in a matter of hours, with the fastest machines placing a maximum of 200,000 components per hour. [167] This can be a good option for PCB's of a certain complexity, but is not a solution for every design. For example, one company had to stop outsourcing to a pick and place company:

> **Company 25:** "Prototyping can be sped up with pick-and-place, but then that same issue comes up. You end up having to do a lot of customization on the pick-and-place machine. Yeah. Prototyping soldering with 1,000 components plus is time-consuming. And we had outsourced, but then, the problem is that ends up not being high-quality work, and then we're debugging someone else's mess. So, that causes more problems... now don't do that. We only do internally, actually, the soldering, because it's too complicated of a PCB for outsourcing."

This example demonstrates the limitations of automated prototyping for new designs. Another example of automation accelerating prototype builds comes from the materials world. Some companies are trying to find the optimal stoichiometries for certain applications, i.e., a lithium ion battery electrode. A robotic system that can do these experiments more quickly and accurately than a human technician accelerates this process. [160] This has become the business model for several startups such as Kebotix [79] which styles itself as a *self-driving lab* that can discover new material solutions with combined AI and robotics.

For many hardware startups robotic and automated solutions offer limited assistance because the system must be highly constrained and controlled which many prototypes are not. Also, startups do not generally have the capital needed to automate their build. This motivates the founding of accelerators, maker spaces, and fab labs which can afford larger and more expensive tools like robotics, machining, 3D-printers, and more. As seen in Chapter 2, over 75% of the hardware startups interviewed have been a part of an accelerator with access to such equipment.

5.3 Testing and Validation

5.3.1 Status Quo

Testing and validation of prototypes can be based on technical or customer testing as discussed in Chapter 2. In this chapter, I focus on technical testing and new tools and methods available to accelerate testing and therefore cycles of learning.

As seen in Chapter 3, technical testing was the second most mentioned aspect of PD slowing down hardware startups. One company leader said:

> **Company:** "Testing takes a long time, [is] slow, we had to automate some of it, and [the manufacturer] had to spend [time] to make their own jig to test the product."

In this quote two significant points are raised: design with testing in mind and automation.

Another company expressed a similar sentiment when asked what their limiting step in prototyping was:

> **Company 25:** "It is testing. It's definitely the largest but the most time consuming. We've hired a lot of co-ops and we have 17 [prototypes] back there... So at this point we are paralyzed to the point where one chemist can't learn. It's hard to come up with 17 insightful experiments without the results from the first one."

In this example, the company had to pause the entire prototyping process, until results could be attained from one experiment. This reveals another potential target for acceleration in testing: parallelized testing to attain more data per unit time. One final lesson learned from the interviews is the importance of choosing appropriate metrics to test. It is essential to validate any new design, understanding the metrics that are important, designing towards those metrics, and having the capability to test for them. One company in this study went after the wrong metric for over a year, losing development time:

> **Company:** "We had one metric they we were going after and customers weren't interested in that and changed metric. "

This indicates that, during the design phase, one design constraint should be the necessity to test for the important metrics as validated through customer feedback.

5.3.2 Strategies and Tools for Future Testing

With the widespread availability of tools such as sensors [111], microcontrollers [103], and software packages [66], hardware startups can collect more data on their metrics of interest than ever before. These tools even allow for automation of testing in some cases. Not only is it faster and potentially more accurate, automated testing can continuously feed data back into the design process.

With the collection of large amounts of data per unit time and potential addition of automation, multiple cutting-edge computational tools become useful for diagnosing system issues and giving feedback for future iterations. This ultimately accelerates troubleshooting and decreases the time between prototype iterations. Also, this can reduce reliance on complicated and incomplete system models as well as human-determined heuristics, informing the next iteration. The machine learning era has brought about many tools that, coupled with large amounts of data from testing, enable predictive analytics to accelerate development.

5.3.3 A New Testing Method for Solar Photovoltaics

The market of solar photovoltaics (PV), like most Cleantech sectors, was hit by the hardships described in Chapter 1. An account of the difficulties in this sector are detailed in Appendix B including specific case studies highlighting unique problems facing the industry.

In the remaining chapters of this thesis, I present an acceleration tool for PV testing that enables more data collection than current standard testing of PV cells and modules. This tool, called Representative Identification of Spectra and Environments (RISE), creates more data per unit time in the "testing/diagnosis" step of photovoltaic system development, allowing for more accurate testing with potentially similar testing throughput at scale. In this method large amounts of measured data are clustered using a ML algorithm to statistically represent all outdoor conditions for a reduced number of indoor tests. This tool is a specific example of using computational methods to accelerate PD.

5.4 Conclusions

In this chapter I have presented a prospectus on technical tools that have been, and continue to be, developed to accelerate product development.

Starting with the design step, 35% of companies interviewed think designs were killed off too quickly and 58% of interviewees thought designs were pursued too long. This indicated shortfalls in some of the interviewees' ability to both explore the entire parameter space, and to down-select concepts to prototype in the desired time. I reviewed some of the cutting edge resources that are enabling designers to explore more of the design space and down select concepts to build faster. These include expert systems, case-based reasoning, generative modeling, other machine learning assisted design tools, and CAD visualization .

Next, I explore the build step, including 3D-printing and automation. I found that without prompting through the interview questions, 20% of the interviewees brought up the importance of 3D printing to fast iteration. Two specific limitations were raised about 3D printing: part reliability and integrity as well as the fact that if DFM is not accounted for, these parts cannot actually be manufactured. Automated solutions were found to be of limited help because the system must be highly constrained and controlled which many prototypes are not. Also, startups do not generally have the capital needed to automate their build. A couple of exceptions I found include the use of pick and place machines for simpler PCB manufacture as well as a materials startup that uses some robotic systems to perform experiments more quickly.

Lastly, I look into the testing step which I found was the second most mentioned thing that slowed down hardware startups in 3. I found several directions that acceleration tools for testing could target including design for automated testing, parallelized testing, working to attain more data per unit time, and spending time choosing the right metrics. I briefly suggest some computational tools that could accomplish some of these goals including neural networks that are capable of inferring relationships between input design parameters and output system performance metrics enabling predictive analytics.

In tandem with the strategies found in Chapters 3 and 4, these technical tools and strategies can be used by hardware companies to accelerate their product development. In the next two chapters I describe the RISE tool I created to accelerate product development in the cleantech sector of photovoltaics.

Chapter 6

Representative Identification of Spectra and Environments (RISE) for accelerated testing of novel PV materials

In this chapter, a new method is presented for classification of solar spectra that takes millions of spectra and finds a representative set that describes the entire dataset. This method, called the Representative Identification of Spectra and Environments (RISE) overcomes some of the limitations of spectral classifiers used by academia and industry.

6.1 Motivation

Performance of photovoltaic (PV) technologies varies due to outdoor operating conditions, specifically, the temperature, irradiance of the sun, and the solar spectra hitting the cell. The effect of temperature and solar intensity on solar cell performance have been studied in depth as they are the largest determining factors [33][54][141]. These two parameters are captured in solar testing in a variety of ways. Differences in performance due to temperature have been quantified using linear temperature coefficients found for each technology. While for varying intensity, the number of sun hours per location or tabulated intensity in W/m^2 are used. The effect on PV performance of spectral composition of the available sunlight is not as well studied, and rarely taken into account during testing [38][4]. The shape of the solar spectra depends on the time of day and climate at the location in question including humidity, cloud cover, surrounding albedo, and aerosols. [121] The various spectral shapes effect solar materials differently based on the band gap of the technology. Spectral impacts on performance have been demonstrated to account for differences in power output of up to 3.4% when compared to the standard spectra used in testing (AM 1.5) [31]. Other literature suggests greater that 6% energy yield differences between technologies due solely to spectra variations [63]. Even though these effects are significant, many tools for PV energy yield predictions neglect spectral effects and there is no standardized method for characterizing the effect of spectra on a solar cell.

The spectral effects on different solar cell technologies can be inferred from Figure 6-1 where the external quantum effeciency (EQE) (top) shows the wavelengths in which technologies absorb. The different shapes of solar spectra for different locations (bottom of Figure 6-1) show how this can affect performance. For example, the spectra from Singapore, depicted in red have lower irradiance at higher wavelengths due to water absorption bands in this very humid climate. This disproportionately effects the materials that absorb above 800 nm such as Silicon and CIGS as seen in the EQE.

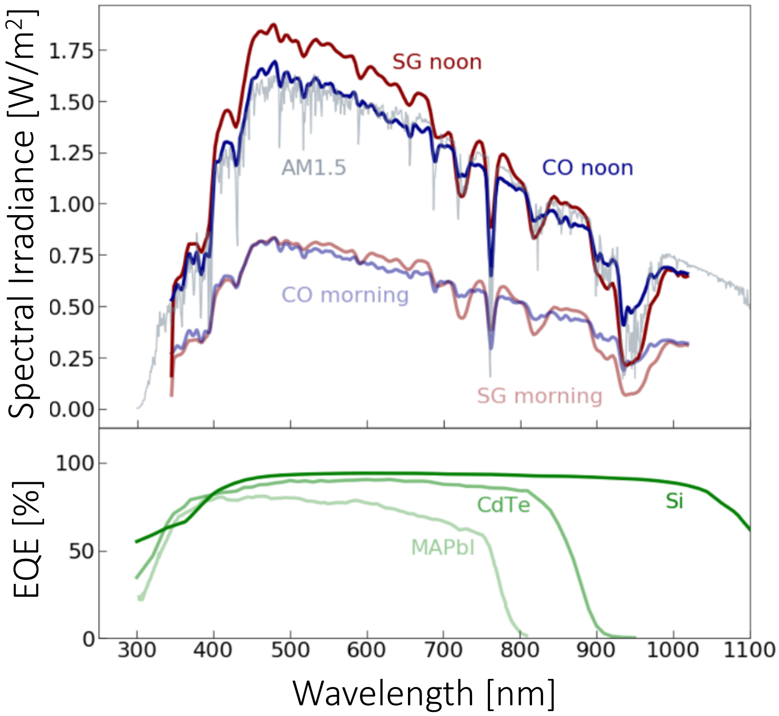


Figure 6-1: External Quantum Efficiency and Spectra Examples

Top: Several spectra from different locations (humid Singapore and drier Colorado), and different times of day show the varied shapes of shifted spectra. Bottom: EQE of several technologies showing how there are differences in how well these materials absorb [108][132][76][165].

The spectral effects on solar cell performance have become increasingly important as technologies become more efficient and solar PV powers more of the electricity grid. In 2017, solar modules reached a global cumulative installed capacity of 398 GW, generating 460 TWh, or about 2% of global power output. Solar power generation is expected to grow to between 800GW and 1TW by 2023 [12]. With more of the power grid dependent on this growing sector, every performance difference due to outdoor conditions between different solar cell materials and architectures begins to matter more.

As new technologies and architectures are brought to market, it is important to quantify the spectral impact on the performance of these technologies. To accomplish this goal, a unique classifier is needed for solar spectrum characterization in different climate zones worldwide that can be used to quantify performance differences between technologies. The method described herein, RISE, meets these criteria.

6.2 Existing Classification Methods

In industry, a standard solar spectra called Air Mass (AM) 1.5 global (G) is used currently as a part of standard testing conditions (STC) to optimize solar cells [161]. This spectra is defined by the American Society for Testing and Materials (ASTM) G173 under one set of specified atmospheric conditions. The conditions were chosen to be a reasonable average for the 48 continental states in the United States of America over one year. The tilt angle was chosen as the average latitude for these states [7]. This AM 1.5G spectra was generated using a Monte Carlo radiative transfer model with this US-centric set of atmosphere conditions (1.42 cm of precipitable water vapor, sea-level surface pressure and 48.19° solar zenith angle, etc.)[64]. This spectra alone cannot capture differences between different technologies.

6.2.1 Average Photon Energy (APE)

The most commonly used spectrum classification in academia is average photon energy (APE), which can be found by integrating the light intensity and dividing that by the spectrum of the average APE [71][162]. APE is useful for distinguishing spectra that are shifted toward red wavelengths or blue wavelengths, but is insensitive to certain other types of variation. APE is typically calculated in a certain wavelength range [71][162] as seen in equations 6.1 and 6.2.

$$APE = \frac{\int_{\lambda_1}^{\lambda_2} I(\lambda)d\lambda}{\int_{\lambda_1}^{\lambda_2} \phi(\lambda)d\lambda} \tag{6.1}$$

$$\int_{\lambda_1}^{\lambda_2} \phi(\lambda)d\lambda = \int_{\lambda_1}^{\lambda_2} \frac{I(\lambda)}{(hc/\lambda)}d\lambda \tag{6.2}$$

where $I(\lambda)$ is intensity and $\phi(\lambda)$ is photon flux both as a function of wavelength λ, h is Planck's constant, and c is the speed of light. The main limitation of APE is that it is not unique, having an uniqueness only in a limited wavelength range of approximately 450 to 900 nm [31][112][150]. This means that a single APE value represents spectra of different shapes in different locations, making it an unsatisfactory classifier when used worldwide. APE can be used for energy yield calculations if these limitations are considered, as was demonstrated by Liu et al. in 2016 [93].

6.2.2 Simple Model of the Atmospheric Radiative Transfer of Sunshine (SMARTS)

One way researchers in PV have gotten around not having complete spectral data or unique spectral classifiers is by modelling the spectrum directly. The most commonly used model for this is the Simple Model of the Atmospheric Radiative Transfer of Sunshine (SMARTS) [55][56][57]. Using relevant meteorological parameters which are more readily available than spectrally-resolved data, full spectra can be simulated. The simulated spectra can then be used to model PV energy yield, as was shown on numerous occasions [123][122][136][131]. Spectrum simulations, however, do not resolve the issue of a missing spectrum classification or answer the question how to pick a representative set for spectral characterization of solar cells in the lab.

Metrics for spectral conditions are often not considered in the PV market where modules are sold based on the power rating at STC and not how they perform in the real-world. Industry tools such as PVSyst and PlantPredict as well as academic studies described above have started taking spectral conditions into account. However, there is room for improvement in the testing and subsequent performance assessments of solar modules. In this work, I demonstrate a unique classifier of solar spectra that could be used by the industrial and academic PV communities for design and testing of PV modules.

6.3 RISE Method

The Representative Identification of Spectra and Environments (RISE) method uses a clustering algorithm called K-means [95], implemented in sci-kit-learn [118] in the open-source programming language of Python. The K-means algorithm takes measured data points of all spectra and optimizes over the position of the means using a distance metric. In this work, the distance metric used is Euclidean distance and different numbers of means (k-means parameters) are explored.

The first step of the RISE method shown in Figure 6-3 is aligning all the meteorological and spectral data to have the same time steps, and wavelength intervals. Step 2 is the clustering using k-means. The clustering is also done in two parts. In step 2a (k_1-clustering), the raw spectral data is clustered, and the resulting classification sorts largely by intensity or integrated photon current. Due to the prevalence of spectra with low intensity, this clustering will produce many bins with low intensities and few with high ones. This is unsatisfactory for the application of solar module testing where higher intensities contribute the most to energy yield. Therefore, I alter k_1-clustering through the introduction of additional weighting. I modify the step so that the spectra are first binned by irradiance with half as many spectra allotted to each successively higher irradiance bin (k_1-clustering-solar).

Next, in step 2b, called k_2-clustering, the spectra are normalized by total irradiance within each k_1-clustering bin and re-clustered. This second clustering step sorts the spectra by red- and blue-shift. For example, with $k_2 = 3$, designating three clusters centers, the algorithm finds the average spectrum, and each one that is red- and blue-shifted.

Steps 3 and 4 use the unique classification of spectra provided by RISE to model PV devices and calculate energy yield. In Step 3a I find weights for each representative spectra. The weights are the number of spectra from the full data set that are binned in that cluster. Then, in step 3b the spectra and temperature clusters found in step 2 are used to model photovoltaic device IV curves. Step 4 uses these IV curves to predict energy yield and weights these predictions for different locations and times. The IV curves are used to predict differences between EY for different technologies in for example, Singaporean winter and summer in Colorado. These steps are discussed in depth in Chapter 7. The workflow of this method is shown below in Figure 6-3.

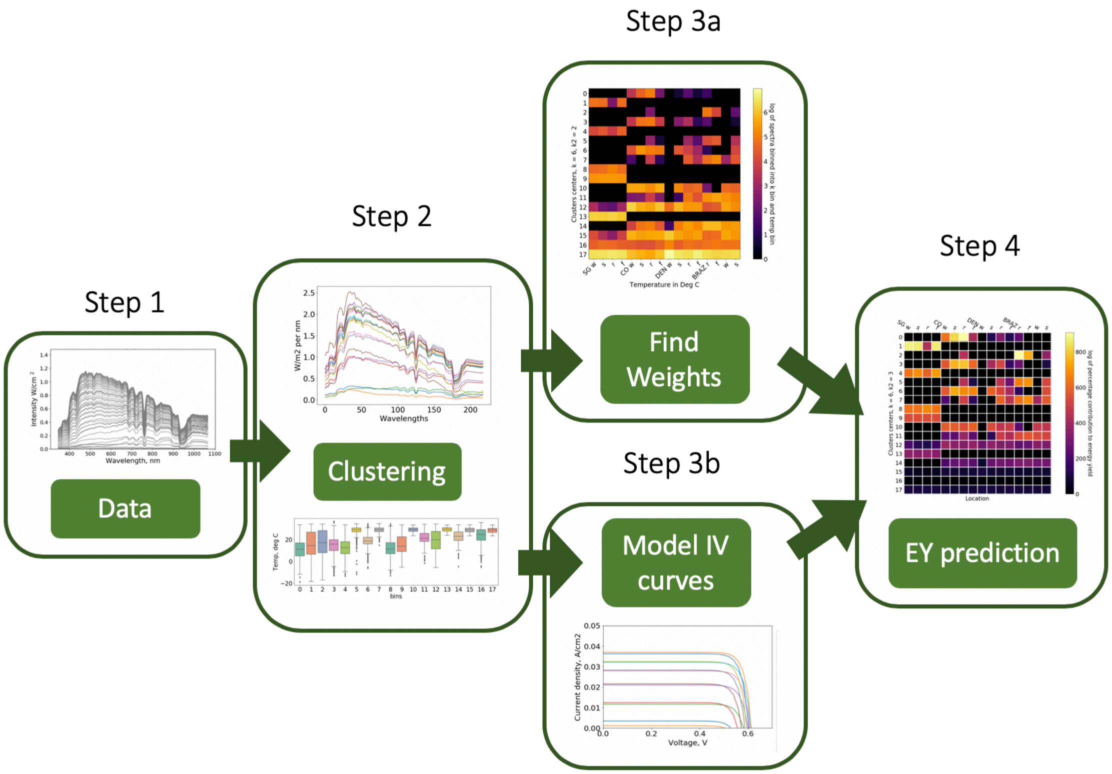


Figure 6-3: Flow chart of RISE Method

The first three steps are data alignment, k_1 and k_2 clustering, and weight finding. Energy Yield prediction for photovoltaics (step 4) is given as an example of an application that the RISE method can help accelerate.

6.3.1 Spectrum Data

The generalizability of the RISE method is dependent on the input dataset, so the spectrum data used should cover as many climate zones as possible. To test my method, I used four spectral data sets for four different climate zones worldwide: cold arid (climate code: BSk, Golden, Colorado), fully humid equatorial (Af, Singapore), equatorial with dry summer (As, Santa Catarina, Brazil), and fully humid warm temperate (Cfb, Denmark).

Each data set covered one year and had a temporal resolution of one spectrum each 30 minutes or better. Comprehensive data sets of measured spectra worldwide for photovoltaics are still scarce, and most research is done with simulated spectra. I believe that this dataset is one of the most comprehensive in the scientific literature to date.

The cold arid dataset was measured by the National Renewable Energy Laboratory (NREL) in Golden, Colorado. Spectra from the entire year of 2018 were measured every five minutes by an EKO WISER system with a MS-711 spectroradiometer that is ISO 17025 accredited. The wavelength interval is 0.73 nm that has been interpolated to 1 nm and the wavelength range is 290 to 1650 nm.

The fully humid equatorial data set was measured by the Solar Energy Research Institute of Singapore (SERIS) in Singapore. Spectra from the entire year of 2018 were measured every minute. The wavelength interval is around 3.3 nm and the wavelength range is around 303 to 1145 nm.

The equatorial with dry summer data set was measured by the Strategic Energy Research Group at the Universidade Federal de Santa Catarina in Florianópolis, Brazil. Spectra from the entire year of 2018 were measured every minute by an EKO WISER system with a MS-711 spectroradiometer. The wavelength interval is around 0.43 nm and the wavelength range is around 285 to 1120 nm.

The fully humid warm temperate data set was measured by the Technical University of Denmark's Department of Photonics Engineering. Spectra were collected in most of the months of 2017. The missing months are filled in by data from 2018 including January 1st through March 14th and June 6th - July 7th. Spectra were measured every 30 minutes with a wavelength interval of around 0.43 nm and the wavelength range is around 282 to 1119 nm.

To perform the classification method described in this paper, the data sets need to be matched in wavelength interval and range. The interval matching is done through interpolation using an interval that is the average of the intervals of all the data: 1.5 nm. The data used in this work is shown below in Figure 6-5. To further generalize this method, spectra from additional locations could be used. I hope that these will become available in the future.

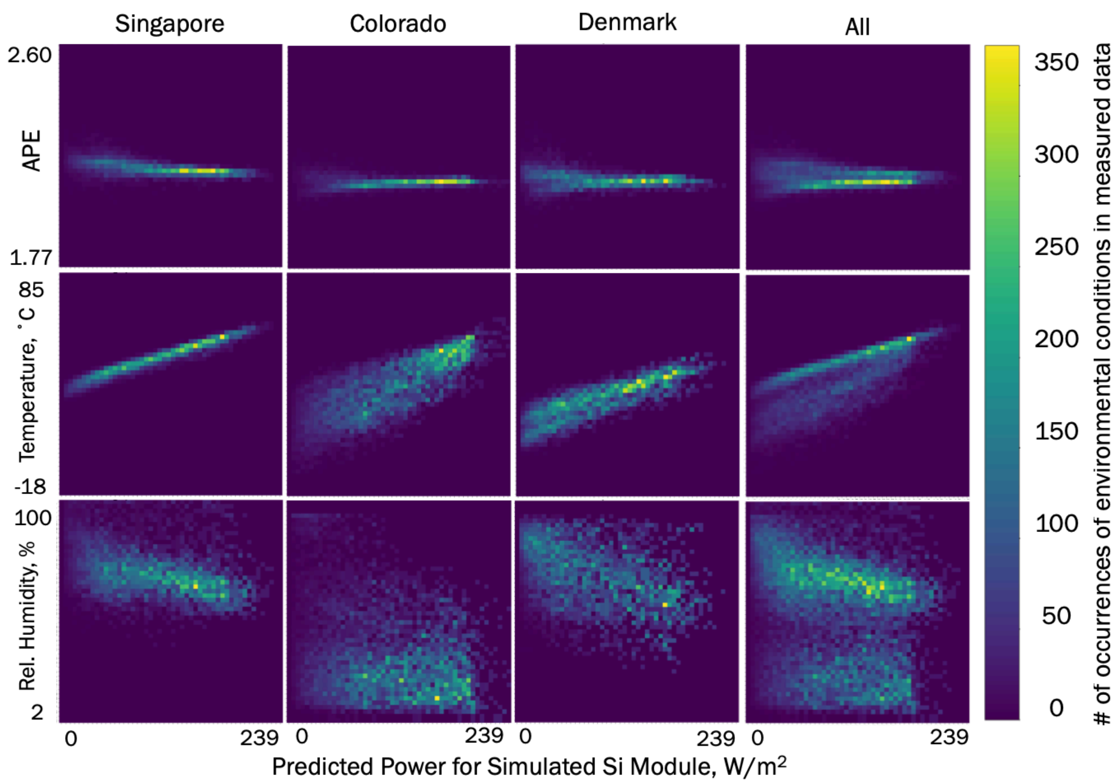


Figure 6-5: Data Used for RISE Method

Data from three of the climate zones (Singapore, Colorado, Denmark) used in this work showing average photon energy, temperature, and relative humidity vs. percent energy yield contribution.

6.4 Spectral Classification and Features

The RISE method with a non-weighted Euclidean distance was first tried on data from Colorado. In Figure 6-7, k_1-clustering and k_2-clustering are shown for five k_1-cluster and three k_2-cluster centers. The k_1-clustering step creates clusters according to irradiance which is reasonable as irradiance is the dominant feature in the spectral functions. The k_2-step cluster according to slope differences. This is reasonable as spectra will have different slopes according to how much light of certain wavelengths are transmitted or absorbed by the atmosphere. As a consequence, k_2-clustering sorts by a physically interpretable feature - a blue-shifted spectrum (spectrum that has relatively more blue light) has a more negative slope than a red-shifted spectrum. The blue- and red-shift of the k_2 clusters are seen clearly in Figure 6-9.

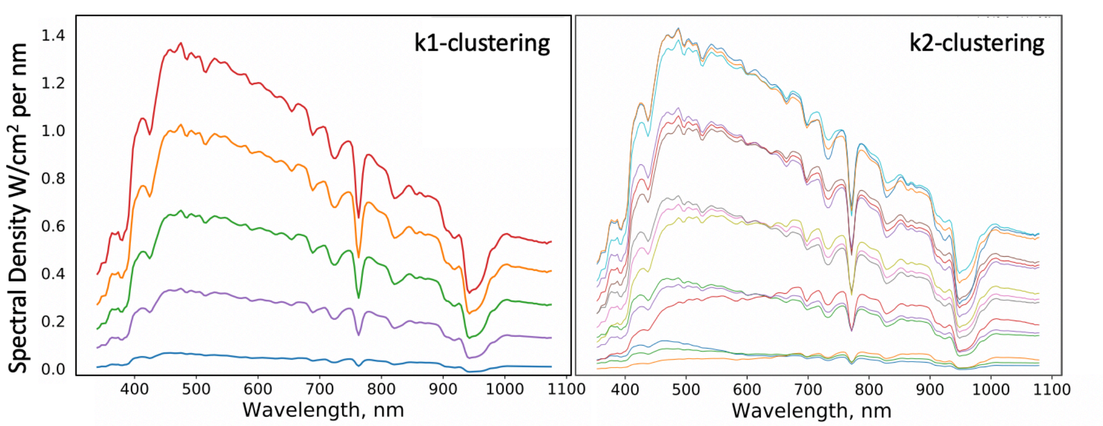


Figure 6-7: Spectra Cluster Centers found with K-means
k_1-clustering and k_2-clustering steps in RISE method.

To visualize how these clusters capture the climate conditions for different locations and times of year, a heat map or "fingerprint" is constructed. To create this map, spectra in each cluster are binned according to location or time.

To illustrate seasonal features, I divide each cluster into twelve bins, one for each month. This is shown in Figure 6-9 using data for Colorado. The intensity of the color of each square in the heat map corresponds to the number of spectra in that bin. A pattern emerges, showing how the spectral shape oscillates between being red and blue shifted over the course of a year. The spectra are blue-shifted in summer and red-shifted in winter.

Another clear pattern is the large number of spectra at low intensities when compared to the relatively fewer at high intensities. Low intensities occur during longer periods in morning and evening, as well as in cloudy conditions. Very high intensities only occur around noon in full sunlight and in summer.

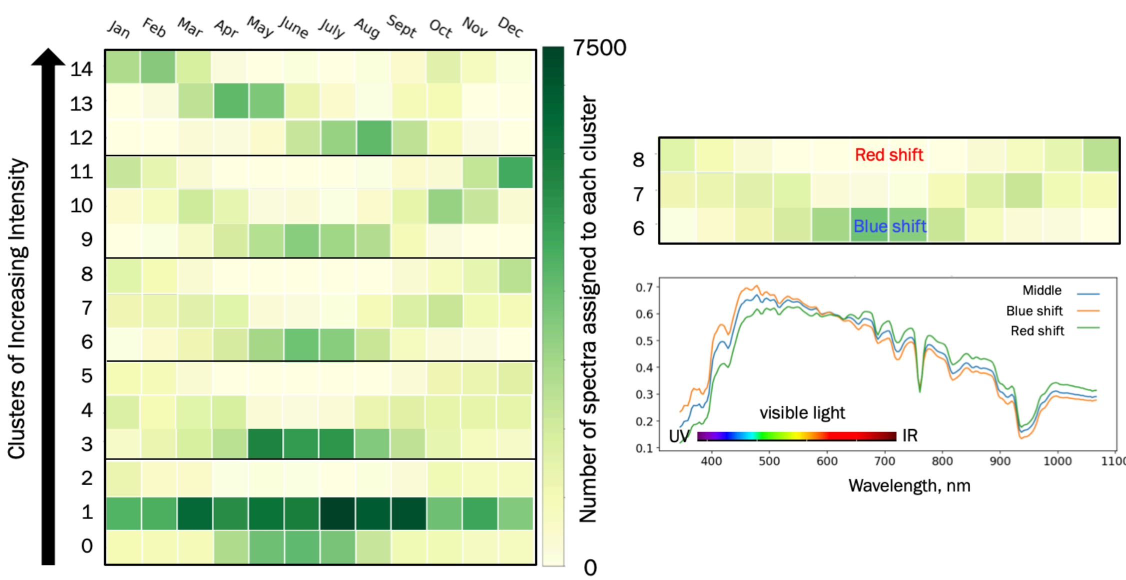


Figure 6-9: Heat Map of Colorado Spectra Frequencies

Left: A heat map showing red to blue shift throughout the year. Right: Corresponding red/blue shift shown in spectra and heat map for bins 7,8, and 9. These are all done for Colorado data.

The ultimate goal of the RISE method is to find one set of representative spectra that can uniquely describe conditions anywhere in the world. With the available dataset, I can find a representative set that describes conditions in the four climate zones used in this clustering. All four data sets from Singapore, Colorado, Denmark and Brazil are aligned into one data set and clustered according to the procedure outlined in Figure 6-3. [1] The results are shown in Figure 6-11. This clustering routine is done for k_1-clustering parameter $k_1 = 6$ (six means used in the first clustering) and k_2-clustering parameter $k_2 = 3$ (three means used in the second clustering).

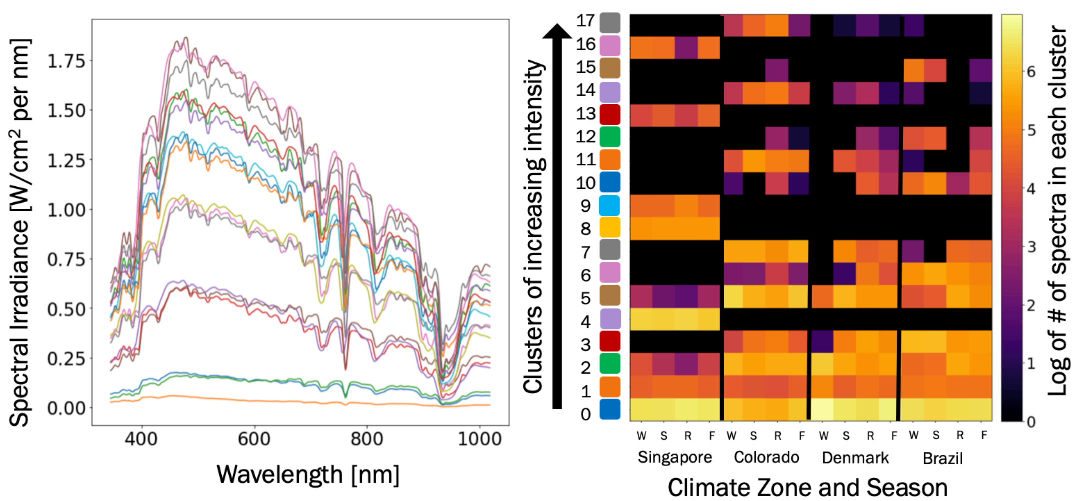


Figure 6-11: Heat Map of Four Climate Zones Spectral Frequencies

Left: Spectra clusters for $k_1 = 6$, $k_2 = 3$. (b) Right: Fingerprint of these clusters and the places and seasons that they fall into. Intensity and seasonal patterns emerge.

One feature of this binning method shown in 6-11 is segmentation of clusters by location. For example, at the highest irradiances (clusters 15, 16, and 17), most of the Singapore spectra fall into cluster 16, whereas for Colorado cluster 17 has

[1] In this case, the "k_1-clustering-solar" step is done in place of "k_1-clustering". The difference between the two is described in the applications section.

the most, for Brazil it is cluster 15, and lastly for Denmark there are barely any higher irradiances. In this segmentation, I expect to see Singapore spectra which are blue-shifted due to high humidity with a more negative slope at higher wavelengths (above 750 nm) than those in other locations. This expectation proves valid for bin 9,10,11 which are light blue, dark blue, and orange respectively in 6-11. Bin 9 has segmented with almost all Singapore spectra, and as can be seen it has lower irradiance values after 750nm in the water absorption bands as expected. This segmentation demonstrates the differences that can arise between spectra in different locations both in intensity and shape. This distinction is especially apparent for high intensity clusters, whereas at lower intensities the spectral shapes are shared between all the locations. This segregation of spectral shape at high intensities demonstrates the difficulty of finding an adequate representative spectral set that can encompass all locations.

However, I do find likenesses between spectra across different locations as shown in bins 6,7,8 (the third highest intensity bins). Here I see that for Singapore, almost all of the spectra in this intensity are in bin 8, but for the other three locations there is a spread between bins 6 and 7. For Colorado, bin 7 is dominant and for Brazil bin 6 is dominant, however for Denmark there is a spread between 6 and 7. In this way the clustering algorithm has found similar spectral shapes at these intensities across geographic locations. In this way the dataset is reduced to a few representative spectra that can represent all the input locations.

Another feature of the heat map in 6-11 is the primacy of sunny hours in summer for all locations except Singapore. For example, going vertically down one column of the heat map for example the summer (R) in Colorado (BSk), it is the highest, considerably above spring, fall, and winter months. This is due to the longer summer hours, and the larger number of sunny days in that season in Colorado. One last thing to note is that this heat map does not obviously reveal red and blue shifts as the single location map did in Figure 6-9. If the map is expanded for all twelve months rather than just the four seasons, the pattern re-emerges.

6.4.1 Evaluation of RISE Classification with Distortion

The RISE method for classifying spectra with k_1 and k_2 parameters for a single as well as several locations has been demonstrated. I can evaluate how well the representative set of spectra captures the input data using a common metric called "within cluster distance variation" also known as "distortion." Distortion is calculated as the sum of the squared distances between each observation vector and its dominating centroid.

The distortion map for the RISE simulations from Figure 6-9 is shown in Figure 6-13. For this map, the RISE method is done with a sweep of parameters from $k_1 = 1$ to 8 and $k_2 = 1$ to 8. Using a map such as this, a threshold value can be defined depending on what the application using the representative environmental conditions requires. In this case a value for distortion is taken to be v = 1.

While the distortion metric mapped in Figure 6-13 shows us how to choose k_1 and k_2 to best represent the spectral data, it does not evaluate the clusters for use in PV energy yield applications. To do this careful knowledge of a physical system is needed for accurate interpretation of results. It is often necessary to provide a new metric by which to evaluate the clusters based on the application. In this case the metric used needs to reflect how the representative spectra found can be used to accurately evaluate performance differences of different PV technologies. I want to understand how closely I can reproduce performance differences due to spectral variations. This evaluation is done in the next chapter.

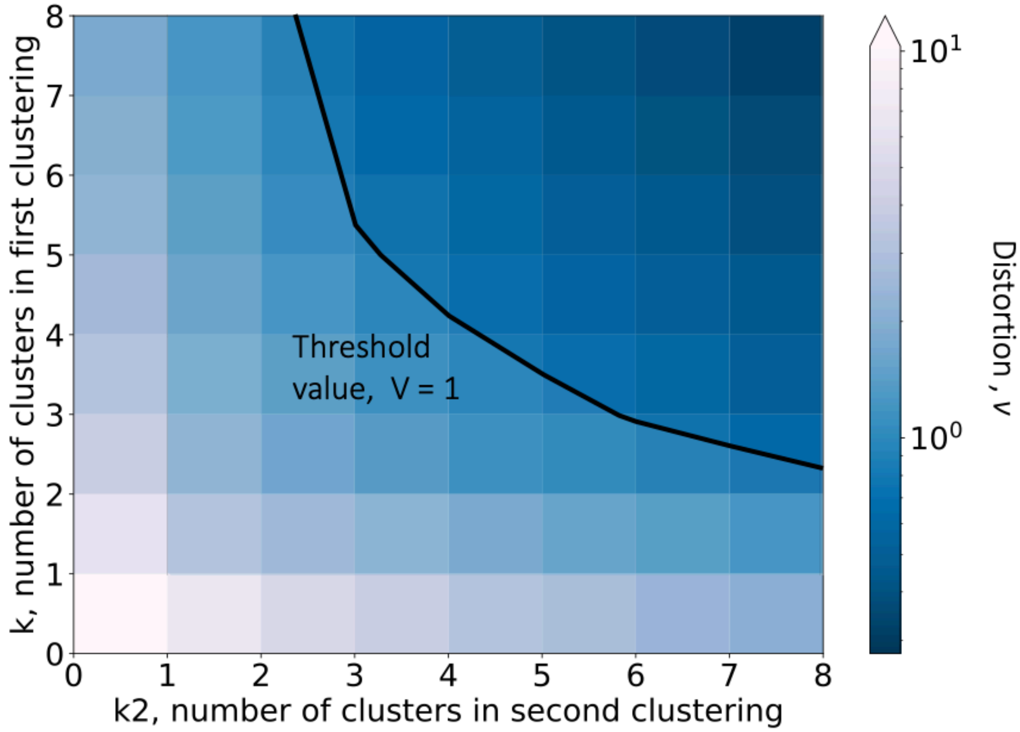


Figure 6-13: Heat Map of Distortion Values

Evaluation of clusters using within cluster distance variation or distortion, and threshold value of v = 1.

6.5 Conclusions

In this chapter, I introduced the RISE method which overcomes the shortcomings of past spectral classifiers used in industry and academia. RISE is technology agnostic and does not need spectral responsivity measurements. Also, the two parameters of RISE, k_1 and k_2 can uniquely classify all spectra worldwide unlike APE. The RISE method could be further generalized to all climate zones by the addition of data sets from new climates around the world. In the next chapter, I show how the spectra found with the RISE method can be used to accelerate data gathered per unit time for solar module testing and energy yield predictions.

Chapter 7

Accelerated Solar Testing and Energy Yield Prediction

In this chapter, I present a way to advance solar testing and energy yield prediction using the representative spectra found with RISE in Chapter 6. The goal of this method is to accelerate the amount and quality of data obtained when characterizing solar cells for both industrial certification as well as in laboratory research and development environments.

7.1 Motivation

There is an interest in the PV industry to improve energy yield predictions, and one way to do that is to account for spectral effects. Several methods now exist to account for solar cell performance differences due to spectral variations. For example, First Solar has taken special interest in this as the manufacturer of CdTe solar cells which, due to the larger band gap, are less sensitive to the spectral impact of precipitable water [110][120]. Similar to the temperature coefficients described in Chapter 6, First Solar created a spectral correction factor in 2016, taking precipitable water and air mass into account for module performance predictions [90]. This calculation can be used publicly in First Solars' PlantPredict tool [41] and a similar method was adopted by PVSyst [104] in October 2018.

On top of the uncertainties of the models that correct for spectral effects, there are large uncertainties in the current STC testing methods on which these correction factors rely. Most solar module testing laboratories use halogen and xenon lamps to test cells under AM 1.5G. However, these lamps do not perfectly match AM 1.5 so to account for differences in testing spectra from STC, a spectral mismatch factor (MM) is calculated giving relative energy loss or gain for a given technology under arbitrary solar irradiance as compared to STC. This calculation can only be done if spectral responsivity (SR) has been independently measured. Large uncertainties exist in MM due to available environmental conditions and available wavelength range for measurement of SR [125][151].

There have also been significant advances in testing with more than just STC for use in industrial standards. IEC-61853 uses a power matrix, measuring module power over several irradiance and temperature conditions. However, all of these testing conditions use AM 1.5 [161]. Also, a Module Energy Ratings procedure was created at NREL with five representative weather days were found to test solar modules: Hot Sunny, Cold Sunny, Hot Cloudy, Cold Cloudy, and Nice. The parameters of each representative day were: air mass, angle of incidence, plane of array, and incident irradiance. With these representative days, a matrix of reference I-V curves is constructed and can be used to translate other technologies to any of these reference-day conditions to determine module energy ratings for more conditions [99]. Though a step forward, both of these approaches used modelled rather than measured data, and the main approach is to correct or translate energy ratings from one measurement at STC.

Rather than relying on correction factors applied to one STC measurement, I envision a testing procedure that encompasses worldwide spectral and temperature conditions with actual measurements. Using LED solar simulators rather than halogen or xenon lamps, allows for tuning of the light used for testing to more closely replicate real world conditions. The SR can then be measured by isolating each LED at a time if needed, making it easier to calculate correction factors for the LED testers [130].

As discussed in the last chapter the RISE method determines a set of spectra that captures the main features of a data set of millions of spectra including the intensity and shape of the 1-D spectral functions. In this chapter, I explore an advancement in solar testing and energy yield (EY) prediction with modeling and experiments utilizing the RISE spectra.

7.2 PV Modeling

7.2.1 Input Parameters

The RISE method can be used for research, development, and testing of solar cells and modules. To use RISE for PV cells, I must consider more than just spectra, and will include temperature data.

Taking the meteorological data that correspond to the spectra in each cluster, I use the spectral bins found in Chapter 6 and search for the temperatures that correspond to those spectra. (The bins in Figure 7-1 are the same 18 from 6-11.) This is done for the parameter set $k_1 = 6$, $k_2 = 3$, for all four climate zones for which I have data and the results are shown below in Figure 7-1.

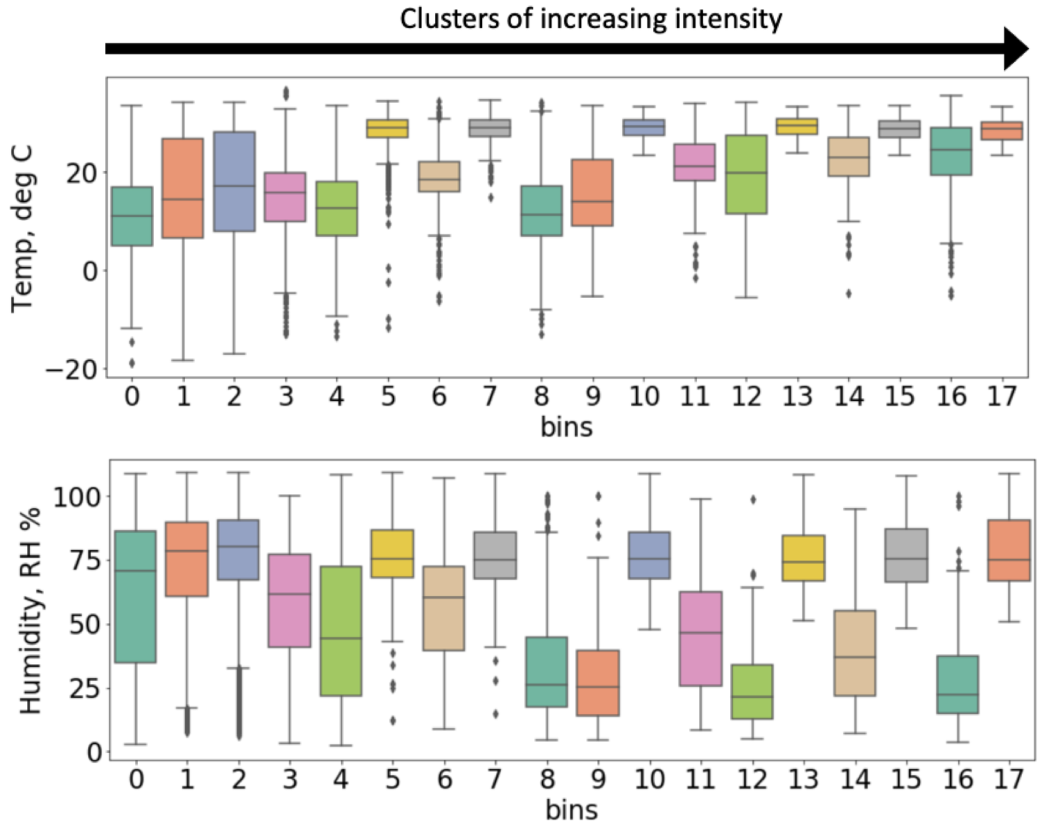


Figure 7-1: Temperature and Humidity Clusters

Ambient temperature and relative humidity's that correspond to spectra bins.

Like with the spectra, some patterns emerge with higher temperatures corresponding to higher intensity spectra. Also there is a clustering of temperature and humidity by location, for example with differences between clusters 6,7, and 8. Bin 7, with higher temperature and humidity and lower variance has mostly data from Singapore, while bin 8 with lower temperature and humidity has mostly data from Colorado. Also, at the lower intensities, there is the largest variation of temperature which also makes sense as the most data points for morning, evening, and cloudy days of all seasons are within these bins. Also, these bins are weighted to have more overall numbers of

data points due to the k_1-solar-clustering step (see Chapter 6).
The temperatures used in EY calculations need to be module temperatures rather than ambient temperatures. Therefore, module temperatures have been calculated from the ambient temperatures using Equation 7.1.[134]

$$T_{module}[^{\circ}C] = T_{ambient} + 0.3 * \int (Irr(\lambda)) \tag{7.1}$$

There are several ways temperature information can be used in EY calculations. The first and most simplistic is just using the average of each temperature cluster. This is implemented as a first approximation.

7.2.2 One-Diode Model

Now that I have the needed input parameters, I model solar cell performance under the representative conditions. I use a one diode model shown below in Equation 7.2.

$$I = I_{ph} - I_0(e^{-q(V+IR_S)/(nk_bT)} - 1) - (V + IR_S)/R_{sh} \tag{7.2}$$

with I_{ph} as the photocurrent found using Equation 7.3, I_0 as the dark saturation current found using Equation 7.5, q as the elementary charge ($1.602 * 10^{-19}C$), V as voltage, I as current, R_S as series resistance, n as ideality factor, k_b as Boltzmann constant ($1.380 * 10^{-23}J/K$), T as temperature, and R_{sh} as shunt resistance.

$$I_{ph} = \sum ((EQE(\lambda) * Irr(\lambda))/E_{ph}(\lambda)) \tag{7.3}$$

with EQE as external quantum efficiency resolved by wavelength, λ, Irr is the irradiance falling on the cell resolved by wavelength, and E_{ph} as the photon energy resolved by wavelength as found with Equation 7.4.

$$E_{ph} = (hc * 10^9)/\lambda_{EQE} \tag{7.4}$$

with h as Planck's constant $(6.626 * 10^{-34} Js)$, c as the speed of light $(3 * 10^8 m/s)$, and λ_{EQE} as the wavelength.

$$I_0 = I_{0,STC}(T/T_{STC})^3 * e^{((qE_g/nk_bT)*(1/T_{STC}-1/T))} \tag{7.5}$$

with $I_{0,STC}$ as the dark saturation current at standard testing conditions (STC), T as temperature, T_{STC} as the temperature at STC, q as the elementary charge $(1.602 * 10^{-19} C)$, E_g as the band gap of the material, n as the ideality factor, and k_b as Boltzmann constant $(1.380 * 10^{-23} J/K)$.

From these models in Equations 7.2 - 7.5, current-voltage (IV) curves are found with weather and spectral data of the representative clusters. These IV curves are used to calculate efficiency, η, for both Si and CdTe solar cells. Then a temperature coefficient is applied to the efficiency for each technology. For silicon a temperature coefficient of -0.41% per degree Celcius [149], and for cadmium telluride -0.34% per degree Celcius [42] was used.

Once the temperature coefficients are taken into account, these are then used to calculate energy yield (EY) for each of the representative spectra, with the following equation:

$$EY[Wh/m^2 peryear] = \sum_{i=1}^{N} \eta(\Delta n, T, P(\lambda), ...)P_{in}t \tag{7.6}$$

with η as efficiency of the solar cell which is dependent on minority charge carrier injection, Δn (number of electrons or holes injected due to excitation of solar power hitting material), temperature, T, power per wavelength, P(λ), and more. P_{in} is the

total power into the cell in W/m^2 which can be found by integrating $Irr(\lambda)$, where t is time in hours, and N is total number of measured spectra evaluated over.
The Si and CdTe cells were modelled to have the same efficiency for direct comparison. A list of the parameters for these models is in the table below.

Table 7.1: Modelling Parameters and STC Results

Parameter	Silicon	CdTe
Efficiency, %	18.2	18.2
Fill Factor, %	80.6	81.3
Open Circuit Voltage, V	0.565	0.815
Short Circuit Current, mA/cm^2	40.1	27.6
Temperature coefficient, % η lost per degree K	-0.41	-0.32
Series Resistance, ohm/cm^2	1.3	1.215
Shunt Resistance, ohm/cm^2	500	500
Band Gap	1.12	1.5

7.2.3 Energy Yield Prediction

To find a generalized EY for a specific technology, I use the EY calculated for each of the representative spectrum above and weight them using the weight matrices (shown by the heat maps) to calculate a weighted average. For example, in Figure 6-9, looking at the column for July, cluster 0, the number of spectra in that cluster is multiplied by the EY of that cluster. This is done for all the clusters, and then they are added together to get a total energy yield for the month of July. This can be done for any unit of time, and in this work I use the common unit of kWh/m^2 per year.

In Figure 7-3, I implement this first for the Colorado location. IV curves are found using each of the representative spectra and STC temperature of 25°C. A resulting fingerprint for EY contribution with months on the x-axis is also plotted. The red to blue shift pattern is still visible as in 6-9, but now the importance of the high intensity bins in summer months is clearly visible. The spectra that occur in May through August at the highest intensities are up to 5 times more important to solar cell EY than all the other spectra that occur throughout the year.

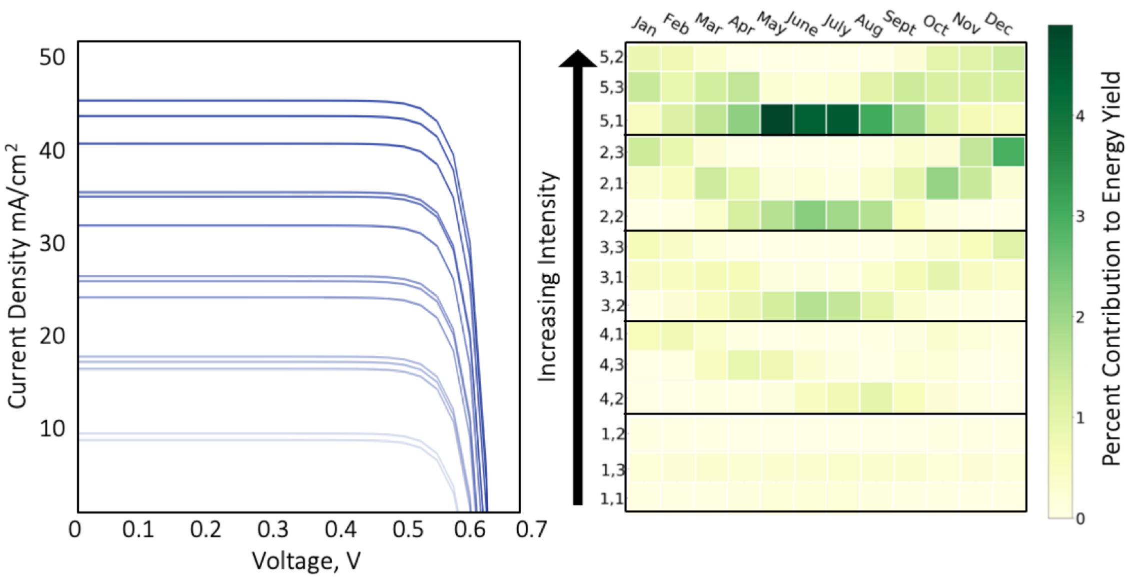


Figure 7-3: IV curves and Heat Map for Colorado Energy Yield Predictions

Left: IV curves for just Colorado data. Right: Fingerprint of the EY contributions of the $k_1 = 5$, $k_2 = 3$ means and the months that they fall into. It is clear that the high intensity bins, especially in the summer are the largest contributor to yearly EY. There are also still clear red/blue-shift patterns.

Next, I extend this analysis to all four locations, using the k_1-clustering-solar step and k_2-clustering steps with parameters $k_1 = 6$, $k_2 = 3$ to find representative conditions, model PV devices, create IV curves for each scenario, and develop the heat map seen in Figure 7-5. Input temperatures are averages of the calculated module temperatures within each individual cluster. With k_1-clustering-solar implemented favoring cluster centers at higher irradiances, there is less of a discrepancy between lower and higher intensity spectra in the heat map than is seen in Figure 7-3. The segregation of the locations and distinctions between seasons are again clearly evident. Figure 7-5 demonstrates in theory the ultimate goal of the RISE method: a measurement procedure that enables EY prediction in any location (encompassed by the input data) with a limited number of measurements.

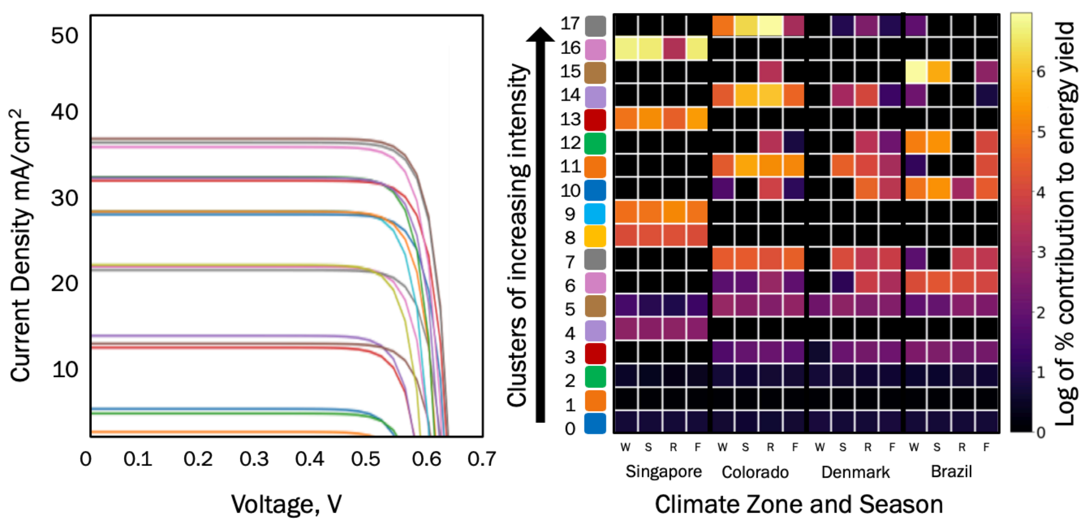


Figure 7-5: IV curves and Heat Map for Several Climate Zones Energy Yield Predictions

Left: IV curves for all climate zones using average temperature within bins. Right: Fingerprint of the EY contributions of each climate zone and season.

7.2.4 Model Evaluation

A first validation of the RISE method for use in EY prediction is the prediction of relative differences between CdTe and Si solar cells in different environments. I show that the representative set of 18 RISE IV curves accurately describes over half a million calculated IV curves ("ground truth") effectively with an average of less than 1 kWh/m^2 error, or 0.52$\pm$ 0.2% when compared to ground truth. This is the accuracy of the method when no temperature coefficient is introduced. When a temperature coefficient is introduced into the modeling, the average difference between RISE EY predictions and ground truth is less than 5.5 kWh/m^2 or under 1.5 $\pm$ 0.5% of overall EY. The errors increase when temperature is taken into account due to the use of only one average temperature for each of the 18 binned RISE spectra as compared to the tens of thousands of temperatures used for the ground truth calculation. This error can be further reduced by using several temperatures for each spectrum rather than just the average.

When compared to STC, the benefits of RISE become immediately apparent especially for use in evaluating which technology to deploy in what location. STC predicts the same EY for both CdTe and Silicon, whereas the RISE predictions captures the different effects of spectrum and temperature on the different technologies. The RISE errors are all much less than that of EY predictions using STC which has an average error of over 17 kWh/m^2 per year translating to over 5% error in overall EY as seen below in Figure 7-7.

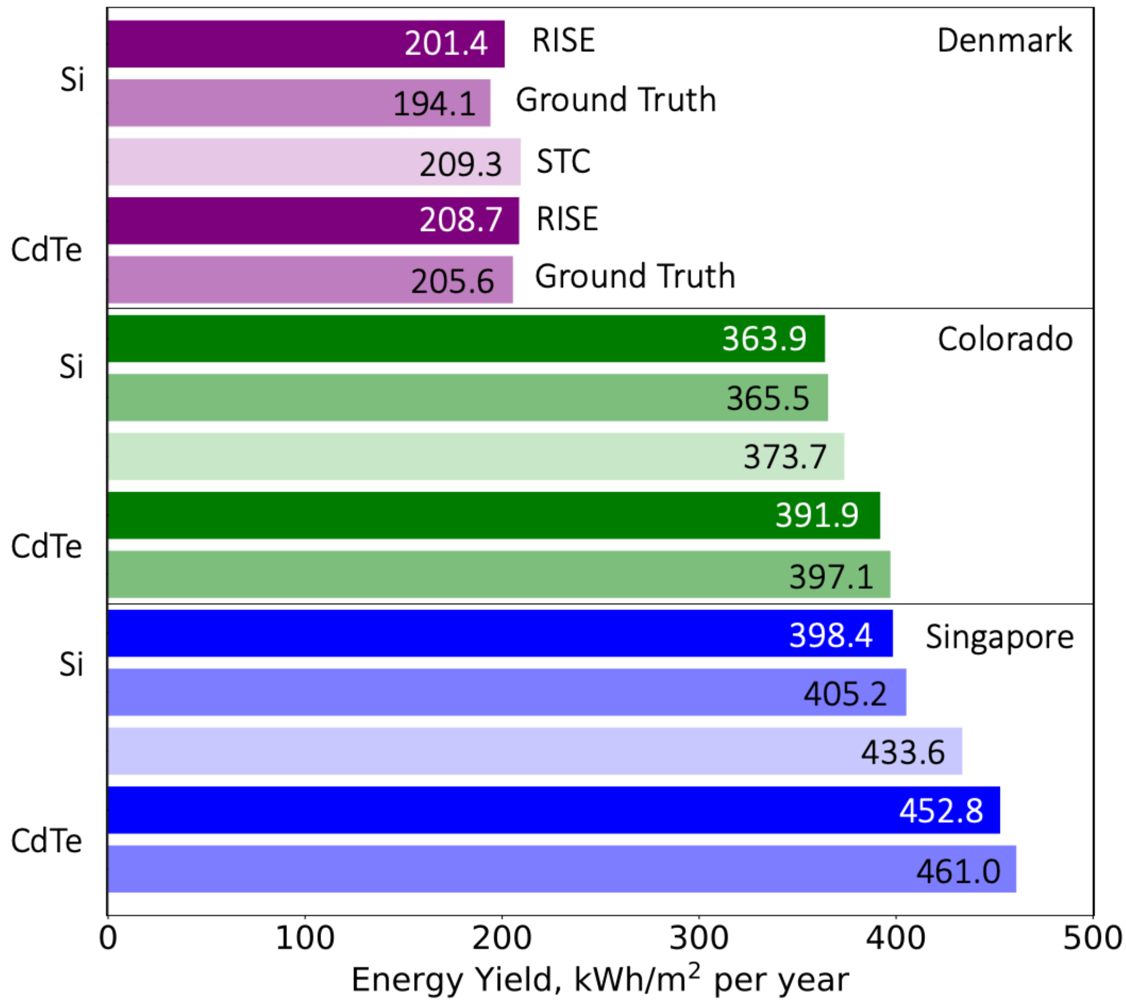


Figure 7-7: Comparisons of Simulated Energy Yield Predictions

In this figure I show the differences in performance of CdTe and Si cells due to spectral and temperature differences for different climate zones. The "Ground Truth" is the EY found when using every spectra and temperature measurement, and the RISE method is using only the 18 representative measurements and averaged temperatures.

As can be seen in Figure 7-7, The RISE method captures the differences between CdTe and Si in Singapore with CdTe performing significantly better, with over 54 kWh/m^2 per year more energy yield. These differences are due to humidity and heat effecting CdTe less than Si technologies. This gap shrinks for Colorado, with around 28 kWh/m^2 per year more energy yield for CdTe. This is less of an advantage for CdTe than in Singapore due to the lesser humidity and cooler temperatures. However, it still performs better than Si because the module temperatures calculated maintain greater than 25°C much of the year. For Denmark, the differences between CdTe and Si are within the error of the model with a slight advantage for CdTe. As a humid location, CdTe would gain some advantage in Denmark, and with the module temperature model used in this work, the average temperatures for modules in Denmark are still above STC of 25°C, also giving CdTe a slight advantage. However, with another module temperature model, this might be reversed with Si gaining the advantage. For example if ambient temperature is used in the modeling rather than module temperature, Si gains the advantage in Denmark and evens out with CdTe in Colorado. In conclusion, the differences between CdTe and Si for the Denmark location are found to not be significant.

Several studies have compared CdTe and Si around the world. Hedegus *et al.* reviewed EY differences in literature between c-Si and thin film technologies including CdTe [60]. The results in Figure 7-7 are in line with the reviewed literature. In the United States, differences between CdTe and Si are found to be small except in hot and humid locations where CdTe gains a significant advantage. A study by First Solar has similar results showing the advantage of CdTe in sunny locations around the United States [143]. In another study by King et al. a comparison of different technologies was done in Albequerque, NM with a climate similar to the Colorado location used in this work. The performance ratio (PR) between Si and CdTe was found to be around 1 for almost all technologies, showing no advantage for either technology in the majority of cases. In another work, Peters *et al.* finds PR differences between CdTe and Si using satellite data. These PR's are qualitatively in agreement with the results of this work. There are significant advantages for CdTe in Singapore and in Denmark there is little advantage to either technology due to the competing effects of temperature and spectrum. One discrepancy is that in Colorado a slight advantage for Si in Peters' work, however this can be explained due to module temperature model differences. If module temperatures are lower than STC on average as they were due to the incorporation of wind in Peters' work, Si has the advantage. In this work, module temperatures used in Colorado are well above STC and do not include wind effects, so CdTe gains some advantage [123].

7.2.5 Experimental verification

To verify that the spectral differences between these technologies can be captured through LED solar simulator based testing, the 18 representative spectra from 7-5 are programmed manually into an LED-based Wavelab Sinus 70 solar simulator, available through collaboration with Helmholtz Institute Erlangen-Nürnberg for Renewable Energy. The Wavelab instrument has 21 different LED's which can be programmed to match a certain solar spectra seen below in Figure 7-9 along side a fit of these LED's to the representative spectrum of bins 6,7,8. To fit the spectra appropriately, the settings of each LED from the AM1.5G default spectra provided by Wavelab are used to calculate the appropriate settings for the 18 representative spectra. While not perfect, the fit of the LED's to the spectra is much better than widely used Xenon or Halogen lamps.

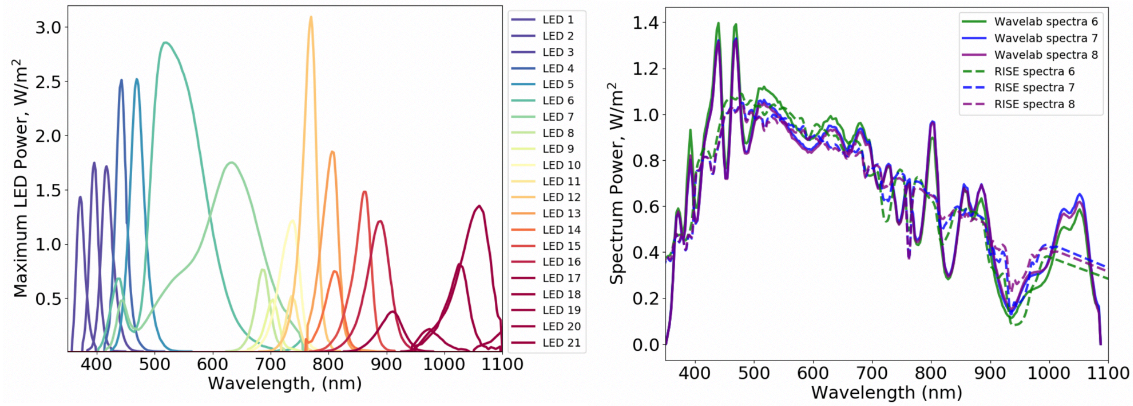


Figure 7-9: LEDs of Solar Simulator and Fits to Spectra

Left: 21 LEDs used by Wavelab Sinus 70. Right: Fit of LED lights vs. a desired representative spectra from RISE method.

Two types of PV materials were tested: Si and CdTe. The Si cell used was a reference cell calibrated by CalLab at Fraunhofer Institute of Solar Energy (FhISE) and the CdTe cells were provided by First Solar, Inc. To test each cell, electrical contact was made with aluminum alloy wire and silver paste. Up to three IV curves were measured for each spectra on each technology and the different shapes between spectra seen in Figure 7-9 are captured visibly by the LED simulator. The resulting IV curves from these measurements can be seen below in Figure 7-11.

As can be seen, the modeled and experimental curves do not match in fill factor. This is due to the measured cells being of a lower quality with series and shunt resistance effects. This is sufficient for our purposes if the current flattens out horizontally to make sure the measured J_{sc} is accurate despite the resistances, the V_{oc} is in a plausible range, and that the arrangement of the different IV curves match in distance and ordering between the simulated and experimental curves indicating that the solar simulator caught the spectral variations as expected by theory. These criteria are met with the figures in 7-11, as can be seen in the IV-curves for Si, for the top three bins, bin 15 (brown) is highest, bin 17 is next (grey), and then bin 16 (pink). This holds true for CdTe as well, however the spread is different. In Si, bin 17 performs relatively worse than for CdTe. This is explained by the blue-shifted nature of bin 17, which makes it impact Si more than CdTe. Another example of the of this is seen in bins 9,10, and 11. Bin 9 (light blue) does the best of this k_1-cluster group in the CdTe cell while bin 11 (orange) does best in this k_1-cluster group for Si. When looking at the RISE spectra, bin 9 has the blue-shifted spectra, and bin 11 has the more red-shifted spectra. The performance differences due to these shifts have been captured by the LED solar simulator as predicted by the one-diode model used for theoretical RISE energy yield predictions. This is good validation of using the LED based solar simulators with RISE spectra for capturing performance differences in technologies in different in environments.

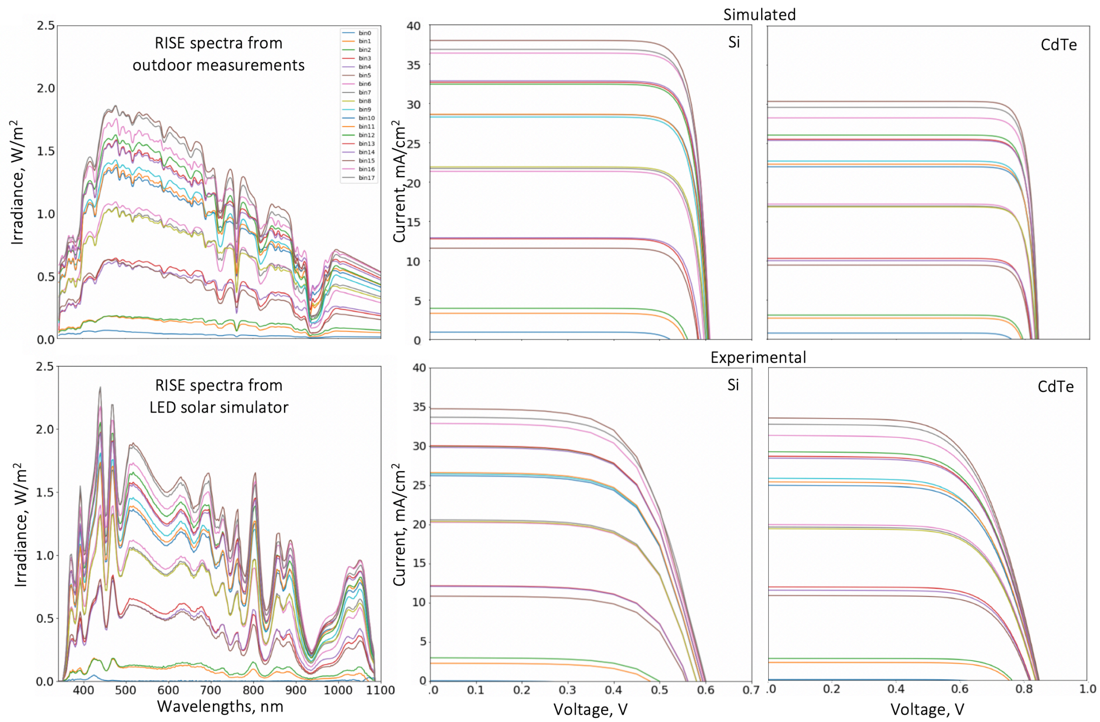


Figure 7-11: RISE Spectra and IV curves Simulations vs. Experiments

Left: RISE spectra as found with RISE method from outdoor measurements (top), and as measured when programmed into the Wavelabs solar simulator and flashed onto a spectroradiometer(bottom). Right: Simulated (top) and experimental (bottom) IV curves of Si (middle), and CdTe (right) solar cells.

From these IV measurements, I extract J_{sc}. J_{sc} as the parameter of interest used to detect the effect of spectral shifts on these technologies. Spectra influences the number of photons of each wavelength hitting the cell and therefore the overall current possible as denoted by J_{sc}. Below is a comparison of J_{sc} normalized by STC AM1.5G for CdTe and Si technologies. In this figure, if the number on the x-axis is positive, then Si performs relatively better in that location in terms of J_{sc}. As can be seen in Figure 7-13, CdTe performs better in Singapore which is expected as this is the most humid location where CdTe should outperform Si and matches our modeling results. It can also be seen that Si is best in Colorado which can be understood due to its relatively dry climate, and for Denmark there is more of a split between CdTe and Si J_{sc}'s, matching the modeling results with no temperature coefficient.

Capturing these spectral difference in the J_{sc} of CdTe and Si with indoor testing of solar modules is a proof of concept for this technique. This demonstrates the potential for these methods to be used within industry or academia in the future to test PV technologies for different climates zones.

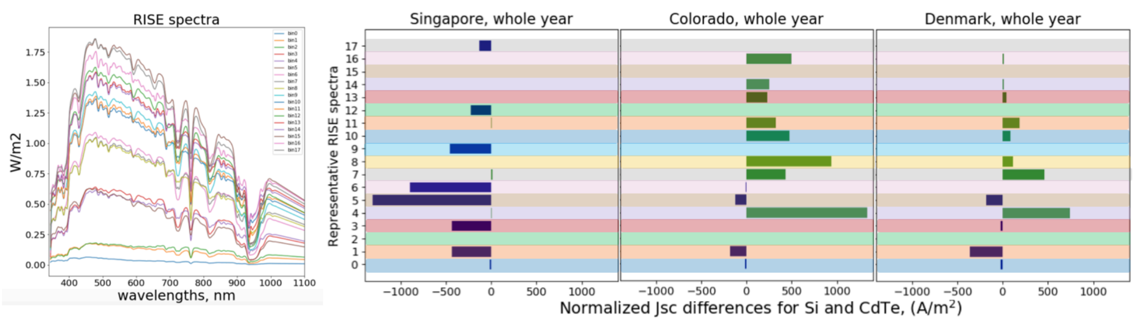


Figure 7-13: Normalized Short Circuit Current Differences in LED-RISE Method

Left: RISE representative spectra, Right: Normalized short circuit current. The colors correspond to the spectra at left so spectra shapes can be matched by eye to advantages in certain locations. (J_{sc}) differences between Si and CdTe.

It should be noted that these J_{sc} differences do not exactly correspond to power out of the cells as temperature effects on voltage must also be taken into account. In a hotter place like Singapore, it would be expected that there would be a CdTe advantage. For places like Colorado, with many days where module temperatures are above STC of 25°C, CdTe would also be expected to have a voltage advantage over Si, while still having a J_{sc} disadvantage. For a climate like Denmark with relatively colder temperatures, Si voltages would not be hurt and might even be helped in aggregate by temperature effects. As can be seen in Figure 7-7, these simulated trends demonstrate the combined spectral and temperature effects in different climate zones as CdTe becomes even better in Singapore, surpassing Si in Colorado. A next step for this work is to measure these temperature effects on voltage during testing with temperature changes implemented in the experimental set up.

7.3 Conclusions and Future Possibilities

In this chapter, I demonstrated a method using RISE and LED-based solar simulators to test solar devices to get more performance data about relevant to real world conditions per unit time than before possible. With this testing process, solar devices can be easily tested with different spectra and (eventually) temperatures resulting in IV curves used to predict EY resolved by location or time of year. The advantage of these EY calculations is that each additional location or seasonal prediction can be done with the same set of measurements, only weighted differently per location or time. This enables a more efficient testing approach for research and development encompassing different climate zones and creating more data per unit time of testing. Using only 18 representative spectra, I correctly reproduce energy yield differences between silicon solar cells and CdTe solar cells with an accuracy of less than $1.5 \pm 0.5\%$ as compared to over 5% when using STC.

I also demonstrate a proof of concept for EY testing using LED-based solar simulators that can capture spectral and intensity differences between different outdoor spectra accurately. With this experimental set up, I capture the relative J_{sc} differences caused by spectral variations between different band gap materials. This is an improvement over current STC that uses just one measurement and extrapolates to other conditions with various energy rating corrections and models. The new LED-RISE method is a promising advance for PV cell and module testing for laboratory or industrial settings.

The next step in this work is the addition of adequate temperature controls to the testing method to emulate the EY modeling predictions in their entirety. Once the temperature ramping is in place, I plan to optimize the testing procedure to decrease overall testing time without losing quality results. This high-throughput testing routine could then be used in laboratories tuning material designs for local environmental conditions or in industry to predict EY for different climate zones, two applications important for the advancement of photovoltaic technologies.

The LED-RISE method demonstrates a technological strategy for accelerating clean-tech hardware product development as outlined in Chapter 5 specifically for the solar photovoltaics sector. By using large data sets, readily available machine learning algorithms, and advances in testing equipment, methods like LED-RISE are poised to bring development acceleration through an improvement in the amount and quality of data acquired, in this case for solar cell testing for energy yield prediction.

Chapter 8

Summary of Contributions

In this thesis, I focused on accelerating the development and commercialization of new "clean" technologies to meet the challenge of climate change. The slow cycles of learning for Cleantech have led to poor outcomes for startups in this sector, and business-as-usual solutions are not sufficient. Through this research I developed strategies both technical and operational for the acceleration of Cleantech product development. To do this, I took a bottom-up perspective from startup companies, focusing on cycles of learning. In this final chapter, I conclude by summarizing my contributions.

8.1 Ch.2 Summary

First, I developed a facilitated survey of over 100 questions using the backbone structure from Ulrich and Eppinger's product development textbook. After testing the questions on several prospective subjects, I edited this survey to ensure clarity and remove bias to the best of my ability. Then, I contacted over 500 hardware startup companies, getting 55 to agree to be interviewed. Through interview audio transcriptions and written notes, I analyzed over 1000 pages to collect quantitative data such as PD workflows and qualitative data through coding.

8.2 Ch.3 Summary

Through analysis of these interviews, I found that prototyping is the largest time investment for hardware startups with a median of 2.5 years from first prototype being started to the fifth completed. I also found that for the first 5 prototypes the median time per prototype was 19 weeks per prototype indicating about half a year of time in companies spend not prototyping between iterations. I then investigated what aspects of hardware development determine these timelines.

Through literature review, I created a set of 16 complexity parameters and adapted a complexity metric. I found that prototyping times are not correlated with product complexity metrics. This suggested that something other than technological constraints determine prototyping times.

To examine this further, I investigated the impact of innovation models on rates of cycles of learning. After extensive qualitative coding in collaboration with sociologist partners, Geoff Raymond and Andre Buscariolli from UCSB, we found a code placing companies on a spectrum from natural to structured innovation. Through analysis of the companies on this spectrum, I found that a flexible, organic innovation model can accelerate early-stage innovation, while a structured PD approach could be preferred for later-stage innovation. However, at some point if structure is not brought into the process, PD is slowed down also. From the interviews, I found several indicators for when structure should potentially be brought into the process. These indicators include when the team expands beyond founding members, when working with outside partners, and when a final fit of technology/market/implementation is reached.

I demonstrated this through a case study in which I found that structure could have sped up the process by preventing overengineering and feature creep. In this case study, bringing structure in after the 2nd or 3rd prototypes could have helped prevent the pitfalls of staying in a natural PD regime too long.

8.3 Ch.4 Summary

Then, in Chapter 4, I found another PD bottleneck in relationships with the key stakeholders of investors, customers, and manufacturers. While these are not new ideas, codifying these relationships as requirements in the traditional sense has not been proposed. I proposed the operational strategy of codifying relational requirements alongside technical requirements during requirement definition as a PD acceleration tool.

Regarding customer relationships, I found alignment in my data with established literature showing that customers need to be a part of PD from the very beginning. Over 83% of interviewed companies used UCD, and 91% talked with customers before starting design showing that the importance of customer relationships is realized by the majority of these hardware startups. However, there were exceptions including one company that waited over four years to first talk with a potential customer. I also found that customer feedback must be filtered appropriately for validity. This is because customers are not always aware of what is possible or what they really want which can cause feature creep and other inefficiencies.

Regarding investor relationships, I found that 40% of companies do not feel pressured to accelerate PD by investors, while 56% do feel pressured. This indicated that active pressure by investors to accelerate PD should be expected, but is not guaranteed. I also found that there is no correlation between feeling pressured to speed up and the actual time to prototype for startups. Furthermore, several companies emphasized the importance of a clear flow of information between companies and investors to develop trust that enables future funding and matched expectations. Lastly, I found that using investors as a source of information as well as money can be beneficial to PD as well as trying the investor-as-customer model enabled by grants.

Lastly, I explored manufacturing relationships. I found that over 66% of interviewed companies claimed to have used DFM, and over 80% used some principles. Through qualitative analysis, I found that neglecting manufacturing relationships that foster DFM can slow down PD. When analyzing the timelines, I found that the median time after prototyping begins when manufacturing is first discussed is 20 weeks, and over 70% of companies did not think about manufacturing until after their first prototype is finished. This indicated that while companies knew about how important manufacturing and DFM was, they often thought about it too late in the process. Lastly, I found that being in close physical proximity to the manufacturer can accelerate PD.

8.4 Ch.5 Summary

In Chapter 5, I presented an outlook for technical acceleration strategies that are cutting edge and have only started to be used by startups. I focused on tools for the prototyping steps of design, build, and test.

For design, I found that the interviewed startup companies wanted tools to explore more of the design parameter space as well as strategies for down selecting concepts to physically prototype. I reviewed several computational tools that could be used

for these purposes including expert systems, case-based reasoning, generative modeling, other machine learning assisted design tools, and CAD visualization which are enabling designers to explore more of the design space and down select concepts.
Next, I reviewed two tools for accelerating the build of prototypes: 3D printing and automation. I found that at least 20% of the interviewed startups rely on 3D printing to accelerate their process. I also found that there is substantial room for improvement for 3D technologies including increased part integrity and integration of DFM. For the strategy of automation, I found that it can be used in a limited way in the form of pick-and-place machines and some automated experiments. However, I found for most startups, robotic and automated solutions are of limited help because the system must be highly constrained and controlled which many prototypes are not. Furthermore, some startups explicitly indicated not having the capital or time for automating portions of the build.
Lastly, I looked at testing. I found that companies could be helped by several testing strategies: collecting more data per unit time, parallelizing the testing process, automating testing, designing with testing in mind, and verifying metrics needed with customer feedback. To implement these testing strategies, I point to the widespread availability of sensor technologies, microcontrollers, software packages, and machine learning techniques for startups to employ in their testing strategies. As an example of one such big data and ML technique that increases data collected per unit time, I developed a solar photovoltaics testing strategy in Chapters 6 and 7.

8.5 Ch.6 & Ch.7 Summary

In Chapter 6, I introduced a technique I developed called the Representative Identification of Spectra and the Environment Method (RISE) using K-means, a machine learning clustering algorithm. The RISE method overcomes the shortcomings of past spectral classifiers used in industry and academia. This method is technology agnostic and the two parameters of RISE, k1 and k2 can uniquely classify all spectra worldwide unlike the commonly used APE classifier.

In Chapter 7, I demonstrated the RISE method in practice using LED-based solar simulators to test solar devices, capturing more performance data relevant to real world conditions per unit time than current standard testing allows. Using only 18 representative spectra, I correctly reproduce energy yield differences between silicon solar cells and CdTe solar cells with an accuracy of less than $1.5 \pm 0.5\%$ as compared to over 5% when using STC.

This proof of concept test of RISE for use in EY testing using LED-based solar simulators captured relative spectral and intensity differences between different outdoor spectra. The next step in this work is the addition of adequate temperature controls to the testing method to emulate the EY modeling predictions in their entirety. Eventually, this testing routine could be used to tune material designs for local environmental conditions or in industry to predict EY for different climate zones.

8.6 Final Conclusions

With the findings enumerated above, this thesis adds data-driven technical and operational strategies to the Cleantech community's playbook to accelerate cycles of learning. Also, a specific tool is developed for accelerated PD in the Cleantech sector of solar photovoltaics. It is my hope that these strategies can help companies to discover, design, and develop new technologies and processes faster and more effectively than ever before to meet the global challenge of climate change.

Through interaction with CTO's and CEO's of hardware startup companies, it is clear that there are many hurdles for these companies that could potentially be lowered. Some of these obstacles are technological, and new tools and capabilities are being and have been developed to make product development, especially the design, build and test portion, more efficient and effective. The availability of high performance computing, the cloud, new and accessible machine learning and statistics tools, automation, 3D printing, and more are promising and exciting new ways for the acceleration of hardware product development. The use of many of these tools is still new for startups and to capitalize on the acceleration they promise will require adaptation and skill-building by the community and educational system. As the world accelerates and automates, so must adaptations by engineers especially if we are to mitigate climate change and build a sustainable future.

Other hurdles that start-ups face are relational, and I have suggested here that engineering universities and industries create codified relational requirements alongside technical requirements. Such requirements may be a new concept for many engineers who may see these as soft, non-engineering tasks. I argue against this perception. The changing landscape of engineering spurned by globalization as well as automation taking over many tasks, means that more engineers are being pushed into what are seen as not "real engineering" roles. Engineers are spending less of their time on the traditional technical work, instead focusing on critical components such as relationship or program management. This is especially true for early stage startups where the limited team size means most team members must wear the hats of many different roles. These teams must develop relationships with potential customers, manufacturers, and investors, all while also designing, prototyping and testing their product. All of these roles require engineering expertise, and should, I argue, be included in the perception of "real engineering," as they are all fundamental to success.

8.7 Research Outlook

This thesis indicates several next steps and research directions. One future direction I am working on is a follow up in-depth interview of several of the companies to investigate specific questions raised in hindsight. Revisiting the companies will allow me to ask questions I wish I had asked in the first round. For example, I hope to focus on their innovation model being structured or natural and how that evolved over time. I also plan to focus on the intensity, frequency, and nature of contact with different partners including customer, manufacturers, and investors. Thirdly, I also want to ask more directly how they have considered, used, or plan to use automation, ML, 3D-printing and other such cutting edge tools. I then hope to follow the companies to their successful exit or failure to provide this as a metric to help inform the findings further.

There is also place for further research into how the new and evolving tools of ML, automation, 3D printing and more accelerate hardware product design. The first step is to implement and document some of the technological tools and operational strategies presented herein. This could be accomplished in the setting of a hardware accelerator for instance in which these strategies could be taught as part of the existing program. Also, in the accelerator setting metrics could be measured regarding timelines of the individual companies in the cohort documenting prototyping times, use of tools, and times to merger, acquisition, IPO, or failure.

Another prerogative set out by this thesis for research groups and engineers is to design and build platforms that make such tools widely useable and available to companies both big and small. Many computational tools have already become widely available within open source langaugues such as Python using free packages like scikit-learn, numpy, TensorFlow, and more. More examples of the application of these tools within academic and industrial settings to accelerate cycles of learning are needed from all sectors.

For example, the RISE testing method is one such tool to be used in academic or industrial settings. The next step in RISE implementation is the addition of temperature control into the LED testing. Next, the ideal number of representative clusters needed to achieve high quality results with high throughput at low testing cost must be optimized. The optimized RISE testing method would then be implemented in a laboratory or industrial setting for use in tuning or selecting technologies for certain environments.

With these future directions outlined, there is work to be done and an urgency to begin as we work toward a sustainable future.

Appendix A

A.1 Cleantech in Literature, A Detailed Review

A.1.1 Cleantech Clustering

Both geographic and meta (internet-based) clustering are strategies for Cleantech companies to leverage resources such as knowledge, venture capital, and supply chain networks, to give themselves a better chance of overcoming the many pitfalls in the Cleantech product development (PD). Geographic industrial clustering is a business phenomenon where interconnected businesses, suppliers, and institutions agglomerate in one geographic area. Economist Michael Porter points to three major advantages to this: (1) increased productivity of the companies, (2) driving innovation, (3) stimulating new businesses. To this end, there have been industry and government led efforts to help the cleantech community form clusters globally. By 2013 there were on the order of 100 cleantech-focused clusters exist worldwide [58][49].

In these cluster areas, accelerators and incubators are commonly found building their own startup spaces (or mini clusters) in one building. Geographer Anna Davies explored to what extent such clustering actually stimulates economic success and creates opportunities for a globally green economy [28]. To study this Davies followed the formation of the first Irish cleantech cluster, the Green Way with 69 semi-structured interviews. Davies concludes that these complex assemblages of cleantech actors, while potentially helpful, are no guarantee toward cleantech success.[105] Even without guarantees, clustering has become a common tactic for hardware startups including cleantech companies because, unlike software companies, hardware needs help accelerating product development and finding patient capital. In Boston, a Cleantech cluster, there are more than a dozen incubators or accelerators, of which at least half are hardware only and two of these are exclusively Cleantech.

Researchers have developed methods for assessing the health of these ecosystems or clusters. In her dissertation, Johnstone explores how to effectively assess the Cleantech Innovation and Entrepreneurship Ecosystem (CIEE) of an area, piloting this assessment in South Africa [74][166]. She assessed ecosystems using existing literature and a semi-structured interviews finding several barriers and drivers for cleantech in South Africa.[1] Johnstone recommended several policy changes to overcome barriers and continue growth [73]. Like Johnstone's work, much of the existing research concludes with recommendations to help new cleantech companies, generally presenting financial or political solutions.

A.1.2 Financial Strategies for Cleantech

Given the poor showing of Cleantech 1.0, many researchers have studied investment in cleantech and suggested reform or abandonment of the VC model for cleantech. Georgeson et al. describes some strategies VC investors have taken to lower the risk of investing in cleantech like sharing knowledge or co-investing to reduce overall risk,

[1]Barriers she identified included a miscommunication between stakeholders, misalignment of purpose and targets within startups, inequity in access to markets, and a risk-aversion in funding cleantech startups. Drivers she found for cleantech included good infrastructure, strong institutions, and widespread support of cleantech among many actors.

establish trust, and allow for fast opportunity identification [50].

Gaddy et al. advocates for abandonment of VC model altogether and the introduction of new investors including institutions such as pension funds, sovereign wealth funds, family offices, and charitable foundations. Another strategy put forth is partnership of large companies and smaller cleantech firms through investment or acquisition. For example two international oil companies, Total and Exxon, partnered with Cleantech startups in batteries and carbon capture, respectively [128][100]. Another strategy Gaddy et al. put forth is government and other patient capital supporting private and non-profit cleantech incubators/accelerators that give startups access to needed equipment and space and potentially capital. This is in line with the idea of cleantech clustering for success: "Indeed, if cleantech entrepreneurs can use shared resources from federally funded research centers, university labs, private research institutes, or incubators, they can avoid the VC countdown clock to exit." [48]

Ghosh et al. also points to the need for patient capital, but acknowledges that this would mean VC funds could take on less companies overall, impacting their bottom line. Also, the funds will need to be larger to support the capital intensity of these companies "All of these factors imply that if VC investment in the energy sector is to be sustained in the absence of early exit opportunities, it will require a radical reworking of the VC fund structures and terms." [51] Ghosh et al. argues that if these timelines are to be so long, then one critical part of the solution is government support to ensure a number of good exit opportunities for these startups through (1) stable long term policy measures and (2) incentives for utilities and others to be first adopters of new technologies.

A.1.3 Policy Strategies for Cleantech

It has been shown that interventions through policy like those above can stimulate investment in cleantech innovation [107]. Two major directions these policies take are: regulations and incentives. Economist mostly agree that incentives that are flexible are more likely to work than prescriptive regulation.[67] There are two things these policies most aim to do: induce creation of clean technologies which can be measured by patents (R&D) and drive the adoption of already developed clean technologies. Complying with regulations has been a confirmed motivator for cleantech innovation and adoptions [6] especially for pollution regulations. Reasons for moving toward cleantech other than government incentives or regulation include company image, reducing cost, and demand pressure.

In one study, Veugelers studies how well government action effects adoption and innovation in cleantech. Veugelers finds that "environmental policy affects technological innovation, but whether a policy instrument is effective or not varies across the clean technologies considered and at which phase of the technology life cycles the instrument is used." [157] This finding is confirmed by Johnstone et al. who found that the effects a policy has depends highly on the specific cleantech technology. For example, the same policies do not necessary work for solar photovoltaics and carbon capture [74].

Veugelers finds that anticipated regulations are the major drivers of eco-innovation in the GHG emission space. In contrast, financial incentives are the best driver of innovations to reduce energy consumption, and it is found that regulation is the number one driver of cleantech adoption. Veugelers also points out that these policy measures can be well structured, but if they are not consistent over a long enough period, they may not be effective. In further research done in 2015, Polzin et. al., finds that feed-in-tariffs rather than subsidies are best for less mature technologies and regulatory codes or standards are best for mature technologies. Lastly they find that long term policy plans with no abrupt changes in policy are needed to get investors to buy in [124].

Appendix B

B.1 Cleantech Sector of Photovoltaics

B.1.1 The Origins of Solar and Cleantech 1.0

The origins of the terrestrial solar photovoltaics industry began much before the word "cleantech" was coined. In his book, *The Solar Generation: Childhood and Adolescence of Terrestrial Photovoltaics*, Philip Wolfe argues the foundations of this cleantech sector were laid in the United States at the time of the oil embargo in 1973 and 1974. The embargo lasted only five months, but the US and other nations had new urgency to develop alternative forms of power to ensure energy security. Due to this oil crisis, four major technologists that worked on solar in the space industry applications started independent PV companies in the US focusing on terrestrial applications. By this point photovoltaics had been used for spacecraft since 1958, but the technology was much too expensive to be provide energy for the grid.[164] Since that time nearly 50 years ago, solar photovoltaics has become another member of the energy portfolio that is transitioning the world from a fossil fuel based grid to a sustainable one. In Figure B-1 below the cumulative installations per year is shown.

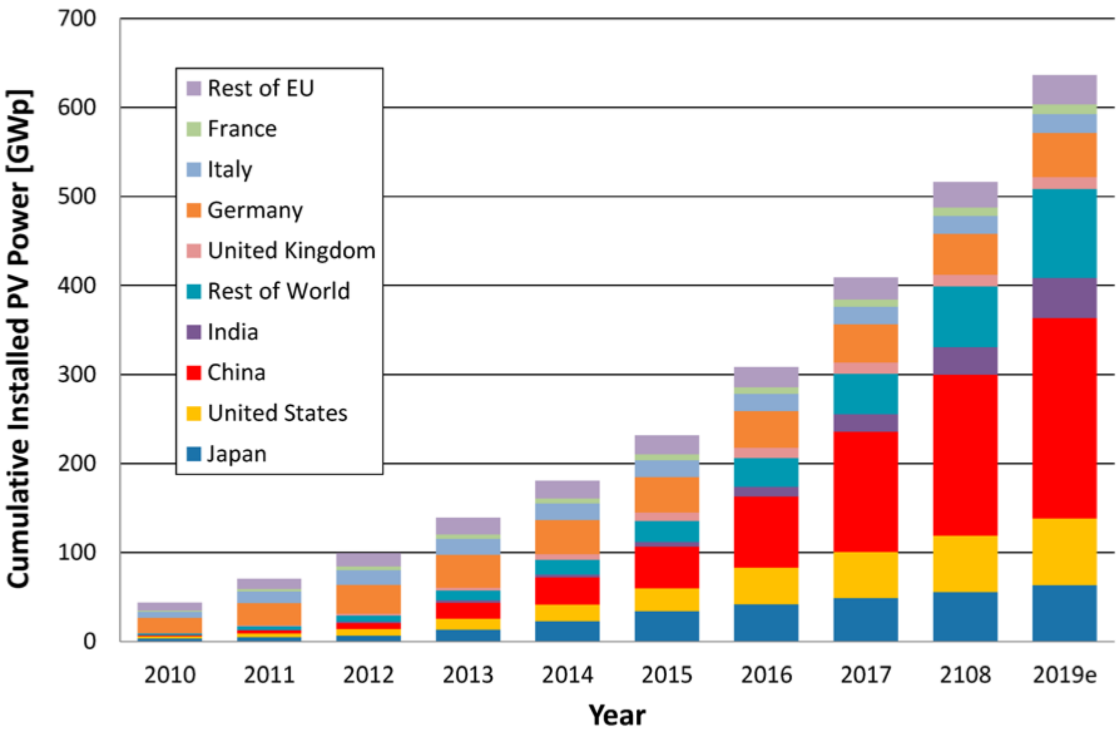


Figure B-1: Solar Installations (2010-2019e)

As of the first quarter of 2019, the world had over 625 GW of installed PV capacity, and this number is expected to double by 2023.[68]

Reasons for this sudden rise in solar installations are manifold driven by concerns for climate change, energy security, fear of nuclear power, and more. However, the thing that has allowed photovoltaics to compete with other energy sources is the decades long drop in prices of solar modules putting grid parity in sight. Many use the "learning curve" B-3 below to demonstrate the module price drop vs. time or cumulative capacity.

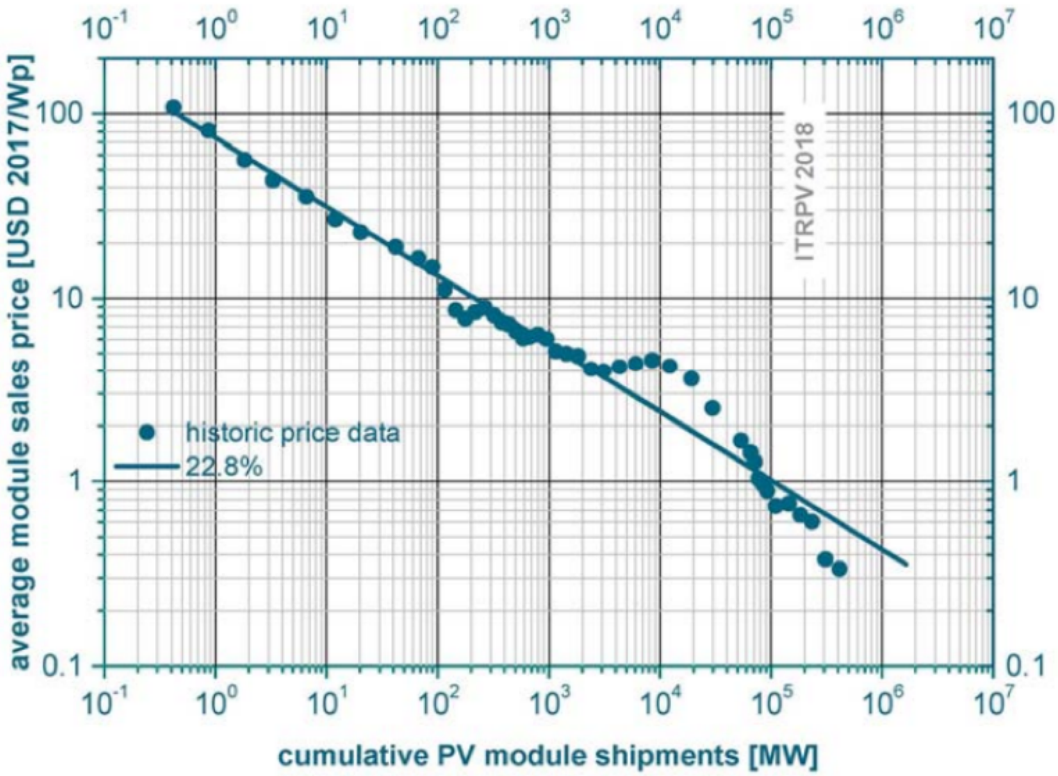


Figure B-3: Photovoltaics Learning Curve

The price of modules dropped below 1 dollar per Watt around 2010 and by 2018 (the last data point on this figure) has reached around 0.35 cents a Watt.[126]

Throughout the years mapped in Figure B-1, the solar industry has gone through a roller coaster of changes. The United States first led the way with much of the original technology patents. Then Europe, and Germany in particular, took a leading role in the manufacturing of solar cells and modules as well as legislated many financial incentives for installing solar. At that time, Japan was the leader in Asia of solar manufacturing. Lastly, in the mid 2000s, China took over as the dominate manufacturing region, far surpassing all others.

Before China took over manufacturing, there was a "solar renaissance" in the United States starting around 2005 as a part of Cleantech 1.0. Many solar startups were popping up around the United States including First Solar, Solyndra, Evergreen Solar, Shell Solar, and more. In this chapter, several successful and unsuccessful photovoltaic startups are reviewed to develop a picture for some specific challenges that solar startups face as they strive to grow into larger corporations. We focus on cell and module manufacturers as well as some system developers including Solyndra, First Solar, Evergreen Solar and 1366 Technologies [68][40].

B.1.2 Solar Company Case Studies

Solyndra

Solyndra was founded in May of 2005 at the beginning of the Cleantech 1.0 cycle. The value proposition of the thin-film solar [1] tube technology was a cheaper price in comparison to the silicon module that dominated the market. The technology was aimed at rooftop solar and was especially attractive as silicon prices had been increasing throughout the decade. In 2009, Solyndra received a $535 million dollar loan from the Department of Energy to cap out at over $1 billion dollars in total investment, and at the end of 2011 the company declared bankruptcy. The precipitous rise and fall of Solyndra presents an interesting case to understand the solar sector.

[1] copper, indium, gallium and deselenide, CIGS

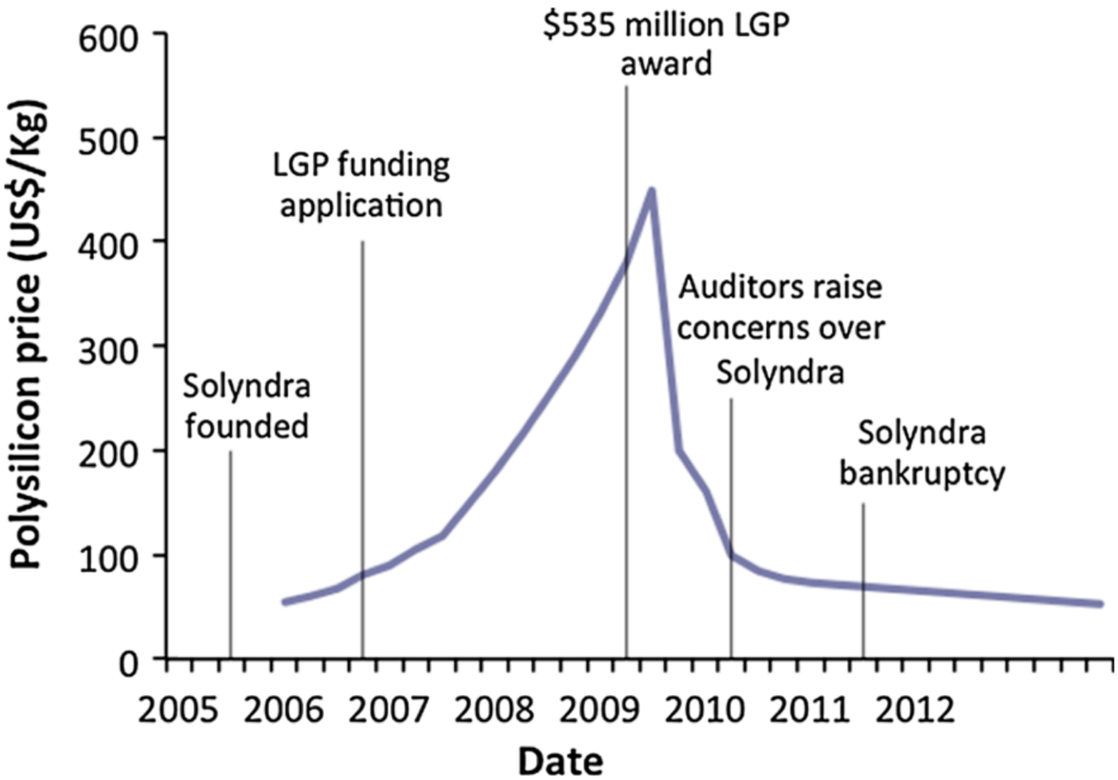


Figure B-5: Polysilicon Price Over Time

Polysilicon spot prices of relevant years for Solyndra [139].

Caprotti, a professor in human geography, identifies key failure mechanisms leading to this highly politicized downfall in a case study published in GeoJournal in 2017 [23]. One of the major sources of failure was the assumption of the value proposition of the Solyndra: that creating thin-film modules is cheaper than the industry standard of polysilicon modules. This can be seen in Figure B-5.

As the price of polysilicon cratered in late 2009, early 2010, Solyndra's competitors could sell their product at a 14 - 20% lower price while still maintaining profit margins. Solyndra's technology in comparison had an overall cost which was about $4 per Watt. And even at a time when the polysilicon spot price had not bottomed out, they could only sell at $3.24 per Watt, causing consistent negative rates of return. According to the Wall Street Journal's reporting in late 2011, this reality had been a problem since the company's inception and was overlooked or rationalized as a short term problem by the large financial backers including the Kaiser foundation, Goldman Sachs Group, Madrone Capital (of Wal-mart), and Virgin Green Fund (of Richard Branson) [23].

The reality of their overpriced panels and falling price of polysilicon panels led to a decision point in the company: (1) keep existing operations in place and work toward drastic reduction in costs, or (2) expand operations to use economies of scale to become a market leader. It is reasonable to assume that the company had very little ability at this juncture to enact choice (2), but "the perfect storm" of factors came together as the US government was looking for clean energy startups to invest billions of dollars into. The reason for this was a 2005 federal loan guarantee program (LGP) authorized at $4 billion dollars for nonpolluting energy sources. Originally envisioned for use in nuclear energy, the LGP was revitalized in 2009 with the Obama administrations economic stimulus and expanding interest in clean energy. The LGP fund was eventually expanding to $16 billion dollars of which over 3/4ths of the funding went to solar projects [23]. The injection of over half a billion dollars from the federal government, renewed faith in Solyndra by private investors, and the company expanded, building a new factory in California. However, by this time, the company could not even sell the inventory of modules from the first factory in the hostile market environment. The new factory opened in September of 2010, and by August of 2011, the company filed for Chapter 11 bankruptcy laying of 1,100 employees and shutting down all operations [102].

Looking at the case of Solyndra, points of failure for this company can be associated directly with the three reasons that venture capitalists(VC's) and others believe

Cleantech 1.0 failed as outlined in Chapter 1. (1) The fact that VC's and other investors in Solyndra did not understand the technology to a sufficient degree can be traced to the major investments by private equity as well as the US government in the Solyndra technology that was not profitable even with substantial feed-in-tariffs. A significant drop in module manufacturing cost vs. module price was needed for the company to be profitable. (2) The long timelines of development for hardware and cleantech specifically were not considered adequately either. This is apparent in the fact that the company and its investors, notably the US government backed expansion of the company's operation within 4 years of incorporation over a conservative approach to consolidation and short term profitability. (3) The marketplace of energy greatly hurt Solyndra's business model's profitability. At the point of Solyndra's ramp up, the financial crisis had hit, polysilicon prices plummeted, and cheap natural gas availability skyrocketed.

In this 2017 article, Caprotti argues that "green niches" such as the solar energy industry in the case of Solyndra were not appropriately shielded from transnational exogeneous factors. Generalizing this, he argues that Solyndra was not isolated or exceptional, and that "a period of secured and shielded innovative development, including the acceptance of failure, is often necessary in forging societal pathways and new socio-technical futures."[23] This argument aligns with the point of failure number (2): long development timelines for cleantech. Investors and other actors in the cleantech industry must be willing to invest over at least a decade and be tolerant to missteps along the way, including not over-investing too early in the process. Caprotti also points to the need for investment sensitivity to changing domestic international energy markets that fluctuate frequently, echoing point of failure number (3) about the peculiar landscape of energy markets.[2]

[2]The fall out from Solyndra has been notably more political than other company failures due

First Solar, Inc.

I next examine the case study of First Solar (FSLR), a still active company that makes thin-film Cadmium Telluride (CdTe) solar photovoltaic modules. The origin of FSLR was as a glass company which moved toward solar cells in the early 1990s and made their first CdTe module in 2005. The Chief Operations Officer, Tymen deJong commented on the process of proving out a new technology in the solar sector: "The barriers to entry, to figure this all out are years of R & D and hundreds of millions of dollars in capital expenditures. And, to be fair, all of the early efficiency records were based on c-Si...it looked like a better technology to new entrants. But, if you want to look at thin-film, you have to do all that work yourself. Our company leaders had this vision around CdTe and what we could do." [147] Here deJong is pointing specifically to the long development timelines of new hardware technologies and the type of patience and expertise a company and its investors must have to be successful.

In November of 2006, FSLR had a successful IPO, and in 2007 vertically integrated to control many aspects of the value chain including engineering, procurement, construction, operations, maintenance, development, and finance of solar modules and projects. By 2011, FSLR had 36 production lines worldwide. However, the company was not immune to the market forces that were causing dozens of solar manufacturing companies to close worldwide. These included the financial downturn, the drop in polysilicon prices, the rise of inexpensive natural gas, and the dramatic take over within a few years of China as the dominant solar manufacturer in the world. Even before these financial woes, the leaders of FSLR had a conservative financial

to the taxpayer money being lost in its failure. Republican activists used this as an example of government overstepping their bounds meddling in the marketplace. In 2015, the Inspector General's Office issued a report that concluded that Solyndra officials misled the DOE, and that the DOE's process of managing and approving loan guarantees was flawed [39].

strategy. "The reason we pursued a low leverage strategy was because we wanted a strong balance sheet. In contrast, our competitors during this time were levering up and borrowing to expand, and thus had weak balance sheets. People didn't trust those companies. First Solar took the opposite approach." [147] This strategy proved to be valuable as the market forces enumerated above took effect.

Another strategy FSLR took that differentiated it from competitors was vertical integration with two large business segments: components and systems. These two segments had very different market realities. The components market, while higher margin, was also subject to the Chinese take over of the market that was drastically undercutting module prices. However, the systems segment, was less variable and could sustain international market changes and material price fluctuations much better especially due to incoming cash flows from ongoing maintenance, engineering and construction. Furthermore, due to being a components manufacturer as well, the systems segment could create "five percent better performance than competitors because of our intimate knowledge about the panels." Initially, Wall Street criticized then CEO, Mike Ahearn for this move into systems level work and it took several years for this decision to pay off. During this time many investors backed out [147]. During the crux of the difficulties in 2011, the share price of First Solar went down by $4.78, and the company looked as if it were in trouble. However, their conservative financial strategies as well as diversification contributed to saving FSLR from the bankruptcy so many of the other solar companies faced. From 2007 to 2011 sales in systems rose from 0.7 percent to 25.2 percent of FSLR's overall sales showing the importance of this diversification. Also, due to sustained and not extravagant growth, FSLR was able to get the losses under control while still investing in rapid innovation that could keep them competitive.[147]

In 2018, First solar netted an increase per share of $1.36 given a "challenging global

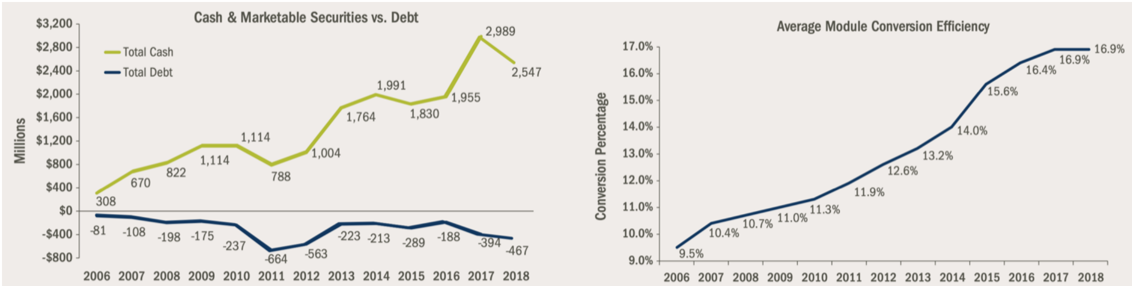


Figure B-7: First Solar Financials

Left: First Solar Securities and Debt from 2006 to 2018 demonstrating the conservative handling of the 2011 market difficulties. Right: First Solar's gains in module efficiency continues [147].

market environment and lower than anticipated production capacity, due to the Series 6 transitions" [147]. The numbers in Figure B-8a demonstrate the conservative financial strategy during the 2010 to 2011 crisis as well as continued technology advancement.

Technology reporter, Adam Lashinsky wrote a piece for Fortune Magazine in 2014 entitled "First Solar Rises Again" which details how the company managed to weather the storm that so many did not. He writes, "First solar is ... a case study in the virtues of marrying wide-eyed technological optimism with patient capital that is willing to see a company through good times and bad." One such investor is John Walton of Wal-Mart fortune that "nurtured the company through years of money-losing research and development and then supported a more recent pivot into a whole new line of business building large-scale power projects" [89].

Looking at FSLR's success in comparison to Solyndra and several other solar bankruptcies, there are several things to be learned in regard to the three pain points outlined in the introduction: (1) lack of technological expertise, (2) long development times, and (3) specific energy market difficulties.

First, the team behind the inception of FSLR were technological experts in thin film technologies. The founder, Harold McMaster, a physicist and mathematician, started working on CdTe in the early 1990s and by 1997 they had a CdTe prototype production machine placing this company years ahead of other thin film R & D efforts. These successes attracted True North Partners, LLC. owned by John Walton with his business expertise in tow, who purchased a controlling interest in the company in 1999 [158]. This leads us to the second point: long development times. While many investors fled, the Walton family "remained steadfast during the lean times." As then CEO, John Hughes said, "Having nearly one-third of your equity owned by one shareholder who has shown a continuing commitment to the company through all kinds of ups and downs inevitably lends an air of credibility and stability"[89]. And thirdly, First Solar confronted the specific problems of the energy market "roller coaster" by diversifying into systems so that a steady cash flow could be maintained even when components are not selling as well. With these three pain points covered through various financial, technical, and business strategies, FSLR has survived in the embattled solar energy marketplace where companies like Solyndra, without strategies to deal with these three pain points could not.

Evergreen Solar

Evergreen Solar (ESLR) is another example of a company that could not make it through the harsh realities of the energy startup landscape. Founded in 1994, this technology push business made proprietary string ribbon solar cells. The technology was created by MIT Professor Ely Sachs who made the ribboning process using half the material needed for traditional wafers. Evergreen opened a manufacturing plant in 2008 in Massachusetts at 80 MW a year with plans to expand even more in the coming years, but by March 2011, they had shifted manufacturing overseas [14] and finally filed for bankruptcy in August of 2011 [88].

There are many reasons that can be given for the demise of ESLR. One of the major ones pointed to by technology journalists at the time was the focus on non-standard sized solar cells that "made the company a small island in a sea of standard component manufacturers." Having a non-standard technology forced any module manufacturer using ESLR cells to create an entirely new and non-interchangeable manufacturing line. With the price of polysilicon plummeting around this time in 2009, the advantage of ESLR's method no longer mattered as much and the disadvantages of having a non-standard component [88].

Other reasons for ESLR's bankruptcy can be traced to the company's insolvency. The company suffered increasing net losses from 2006 until bankruptcy in 2011 [88]. Given this reality, the company could not withstand any major market downturns. And, with the harsh market impacts of polysilicon price dropping and China dominating the market driving prices down by more than 55 percent, ESLR could not turn the ship around.

The major pain points of cleantech companies are present in this story as well. First, the technology, while well known by those the company founders, could have been better fit to the market through the adaptation to standard size cells. Second, the development times for the technology were so long so the ESLR could not compete in the marketplace. The company could not drive prices down enough to ensure cell profitably in time. Lastly, and most obviously in the case of Evergreen Solar, the market realities were so harsh that the company was insolvent for most of its existence.

1366 Technologies

Another technology push company in the solar industry coming out of Ely Sach's lab at MIT is 1366 Technologies (1366 Tech) which was founded in 2007. By 2009, they had developed a proprietary "direct wafer" process by casting solar cells into their ultimate shape within the furnace rather than cutting them from a silicon ingot where $>$ 40 percent of the silicon is lost to "kerf" (silicon dust left over from sawing). At this time they received a 2009 grant from the Department of Energy's Advanced Research Projects Agency-Energy (ARPA-E). The director of ARPA-E explained that "early indications show this could be one of our great success stories" [11]. The company also received a loan guarantee from the DOE's LGP at the amount of $150 million [16].

From 2009 to 2020, 1366 Tech has hung on through a wildly changing market space. Innovation at 1366 Tech has continually shown promise throughout the decade with tunable thickness wafers and high efficiencies. At this point, the wafer furnaces are industrial-sized machines at generation three. The company was slated to build its first full scale commercial factory in 2017 in upstate New York, however this plan was stopped due to the inability of the company to meet the requirements of the renegotiated federal loan in 2018. However, the company persists today and is working with other solar companies to continue toward commercial adoption.

There are several consistencies with the outlined cleantech pain points and this company's journey. The most obvious is the long runway needed by 1366 Tech, which has been incorporated for over 12 years now with still no commercial production line. Even with the backing of the DOE and many private investors as well as stellar IP and highly trained scientists and engineers, the company has struggled to produce. Another point to note is that with the back drop of the roller coaster of the solar market, the company has also been lucky to have patient capital that believes in the company's technology and its viability in the marketplace.

B.1.3 Discussion/Analysis

Through these four case studies, it is demonstrated that the cutthroat sector of solar energy is a good example of the difficulties facing cleantech companies more generally. The market forces these companies faced were catastrophic including the precipitous drop of polysilicon prices and unfair advantages given to Chinese companies through government backing. Compounding these problems, the technology risk was poorly understood by investors and the time it took to develop these new technologies and get them down to market cost were too long to be competitive.

There are specific lessons for Cleantech stakeholders to take from these case studies. One lesson is that the influx of so much funding during the still early development stages of Solyndra did not help them as they took it as a sign to expand when their current operation was not making money. Another lesson is that First Solar's approach of conservative accounting, and diversifying their portfolio to include the systems business has so far saved them from the fate of Solyndra, and is a good example of sound strategies for staying alive in this marketplace. A third lesson, learned from Evergreen, is that to succeed in a low margin, commoditized market, the product needs to be standardized as much as possible to fit into existing manufacturing lines. And lastly, for all the companies, the development runway for their technologies was long and needs be sped up to be competitive.

Appendix C

C.1 Accelerated Materials Development

C.1.1 AMD Introduction

In recognition of the need to accelerate this process, leaders in the academic, public and private sectors have lead work toward solutions for accelerating materials development. For example, in the public sector the Materials Genome Initiative was founded focusing on three specific areas to accelerate the rate of materials search: computational tools, data repositories, and higher-throughput experimental tools. [26] I will briefly discuss some of these acceleration tools for materials and point out parallels and differences with hardware system and product development. Figure C-2a gives an overview of the vision behind accelerating cycles of learning for materials.

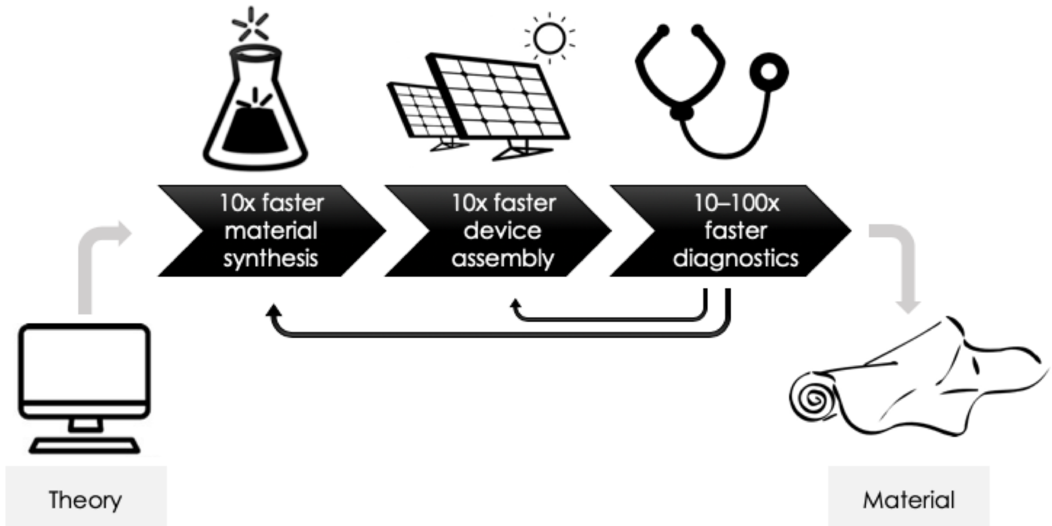


Figure C-1: Accelerated Materials Development

In this schematic we see the three steps of materials development: theory driven discovery, process optimization of synthesis and device assembly, and lastly diagnostics, all within a (ideally) automated feedback loop [26].

The materials discovery step has made progress through faster computation, more efficient and accurate theoretical approaches and simulation tools, and the ability to screen large databases quickly such as MaterialsProject.org [69]. These advances have allowed for inverse design of novel materials [170]. Next, in process optimization for material synthesis and device assembly, acceleration tools are in use such as new combinatorial approaches at large scale, the adoption of solution synthesis, faster serial deposition/reactions, and defect tolerance and engineering [35][72]. Lastly, in the diagnosis step, advancements in characterization tools, use of advanced statistics and ML [116][87], and rapid non destructive testing using Bayesian inference accelerate the characterization and even property predictions for materials development [15][85][86]. As is seen in Figure C-2a, there are continual feedback loops in this work that are ideally automated further accelerating the cycles of learning.

There are many examples of acceleration tools in materials discovery, synthesis, device design, and testing, some of which are shared above. There are many parallels that can be drawn between these steps and system development. As seen in the Table at the beginning of the chapter, materials discovery can be thought of in some ways as system design. In both cases there is a broad parameter space to explore and some set of parameters that can provide an optimal solution depending on the performance metrics that matter. The next step in materials development of synthesis and device assembly can be thought of as the build step for system and product design. In both cases, virtual assemblies can be modeled to test out approaches, and eventually a physical assembly of the material or product must be made. Lastly, the third step of material diagnosis is parallel to the system testing step. For both materials and systems, the use of advanced statistics and ML tools on large amounts of data can accelerate development. In the next section, I describe acceleration tools for system development that mirror those for materials development.

Appendix D

D.1 Examples of Relational Requirements for Adaptation

Below are enumerated some examples of relational requirements for startups to use as a basic outline and example for creation of their own relational requirements.

D.1.1 Customer Relational Requirements

1. The company shall engage with customers early in PD, ideally before concept generation or prototyping begins.

2. The company shall test customer preferences for validity and filter feedback for efficacy through iterative and continuous customer feedback during prototyping.

3. The company should engage with as many customers as possible to not miss any preferences that could be turned into design requirements and cross-validate preferences across the customer base.

4. The company should put physical prototypes in the hands of customers to test and critique as early as possible in PD.

D.1.2 Investor Relational Requirements

1. Once a transactional[1] relationship is in place between the investor and the company, then there shall be contact and review on a mutually agreed upon basis that is codified.

2. Investors should be chosen and then pushed by the start-up to be a source of intelligence that can help with the entire PD process more than just a source of money.

D.1.3 Manufacturer Relational Requirements

1. Developing relationships with potential manufacturers shall be started in parallel with initial prototype.

2. Design for manufacturing (DFM) principles should be adopted in the prototyping timeline by the time proof of concept is complete.

3. DFM shall be practiced with input if not direct supervision from an expert in manufacturing products or a partner from a manufacturer.

[1] A transactional relationship is defined as a relationship where actual goods or services have been exchanged. This means more than just talking or promising things. [43]

Appendix E

E.1 Qualtrics Survey

INTRODUCTION

Welcome to the MIT PVlab Hardware Design Survey!
Thank you for joining us in overcoming the bottlenecks of hardware system development!

Study purpose & why I picked you

The time it takes for new device design is prohibitive for many research groups and startups in the Cleantech energy sector to make impact on the industry.

As a designer, researcher, or manager in an R&D group, you have information that can help us learn the best approach for acceleration! We need metrics rather than anecdotes to do this so your participation is invaluable to collate useful data!

What do you get out of it other than good karma

1. Information on your specific design style, timelines, etc. will be provided back to you easily digestible form for use in your internal strategy going forward.

2. The broader dataset will be available to compare your design style and timelines with similar companies (although you won't know which companies they are, see: Confidentially statement).

3. The survey and results will provide you with exposure to design theory and new strategies for your work.

Confidentiality Statement:

The information you provide will not be shared with identifying information, but rather as anonymized data. If you have concerns about this, feel free to contact me to ask specifics. Thank you for your participation!

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Let's get started!

Section 1: PERSONNEL & COMPANY INFO

Section 1: PERSONAL & COMPANY INFO

What is your name?

What is your highest academic degree?

What field is that degree in?

What company do you work for?

What position do you hold in this company?

How many years have you been involved in this work?

How long have you held your current position?

Where is the company headquartered? (city, state, country)

How many employees does your company have (including you)?

What type of company are you?

- B to B
- B to C

Which of these funding sources do you have? (Pick all that apply)

- Angel Investors
- Pre-seed
- Seed
- Venture - Series unknown
- Series A
- Series B
- Equity Crowdfunding
- Product Crowdfunding

- ☐ Private Equity
- ☐ Convertible Note
- ☐ Debt Financing
- ☐ Secondary Market
- ☐ Grant
- ☐ Corporate Round
- ☐ Initial Coin Offering
- ☐ Post-IPO Equity
- ☐ Post-IPO Debt
- ☐ Non-Equity Assitance
- ☐ Funding Found (catch-all)

How do you procure funding? What is the history of funding for the company?

What was the companies estimated net worth on first market valuation? ($)

What is the net worth now? ($)

Was significant technology or business development done within a research institution or another company before incorporating? Please explain

Are you a member of a incubator or accelerator?

- ○ Yes
- ○ No
- ○ Was in the past

○ Plan to be in the future

What is the name of the incubator or accelerator you are/were a part of and for how many years?

In which categories does your company fit?
(Pick all that apply.)

- ☐ Aerospace
- ☐ Cleantech
- ☐ IoT Devices
- ☐ Medical
- ☐ Software
- ☐ Robotics
- ☐ Developing Nations Applications
- ☐ Other

Other:

In which category of technology do you as a designer predominantly work on?
(Pick all that apply.)

- ☐ Optoelectronic
- ☐ Electromechanical
- ☐ Mechanical
- ☐ Chemical
- ☐ Software
- ☐ Integrated Circuits
- ☐ Printed Circuit Boards

- [ ] Electrochemical
- [ ] Other?

Other:

What would you characterize to be core IP technologies setting you apart from competitors?
(Pick all that apply.)

- [ ] Novel material
- [ ] Novel application/service provided
- [ ] Novel assembly
- [ ] Novel process to make product
- [ ] Novel business model
- [ ] Other?

Other:

When was the company incorporated?
This will be called "day zero" for the rest of the survey. (Don't forget!)

How many hours do workers in your company work in a typical "business day" on average?

Business day: One day of work for the average worker in your company, whether that is during the week or on the weekend, whether it is 6 hours or 15 hours

Section 2: PRODUCT PLANNING

Section 2: PRODUCT PLANNING

What kind of product development is being undertaken? (How do you think about your product?)

- ☐ New product platform
- ☐ Derivative of existing product platform
- ☐ Incremental improvement of existing project
- ☐ Fundamentally new project
- ☐ Other

Other?

What is the competitive strategy of the new product?

- ☐ Technology Leadership
- ☐ Cost Leadership
- ☐ Customer Focus
- ☐ Imitative
- ☐ Other

Other?

What would you name the market segment are you targeting?

Have you ever targeted another market, if so which ones?

Is this a new or existing market?

- New
- Existing

What is the market size in $USD?

What is the projected market growth rate (% per year)?

Competitive intensity of the market (approximate number of competitors)?

Approximately how long after incorporation was the question of which market to target first discussed?

What was the hardest part of targeting a market?

Did you use any specific tools or methodologies to help with market segment targeting?

How important is targeting a market segment to your desired outcome?

- 1 - Not at all important
- 2 - Somewhat important
- 3 - Important
- 4 - Very important
- 5 - Extremely important

How satisfied are you with your ability (the tools and processes available) to target a market segment?

- 1 - Not at all satisfied
- 2 - Somewhat satisfied
- 3 - Satisified
- 4 - Very satisified
- 5 - Extremely satisfied

Section 3: REQUIREMENTS

Secton 3: REQUIREMENTS

Would you characterize your product as a "user-centered" design?

- Yes
- Somewhat
- Neutral
- Not really
- No

Did you talk with customers to understand their wants and needs before starting design?

- Yes
- No

How many months before or after incorporation did you first talk to customers?

How did you gather the preferences of the user?

- Interviewed single potential users
- Focus Groups
- Written Survey
- Other

Other

How important is gathering user preferences to your desired outcome?

- 1 - Not at all important
- 2 - Somewhat important
- 3 - Important

- 4 - Very important
- 5 - Extremely important

How satisfied are you with the tools and processes available to gather user preferences?

- 1 - Not at all satisfied
- 2 - Somewhat satisfied
- 3 - Satisifed
- 4 - Very satsified
- 5 - Extremely satisfied

Were traditional requirements identified and targeted for design?
By traditional I mean engineering style with the should, shall, will words (like NASA uses). If you don't know what I'm talking about.. then you didn't use them.

- Yes
- Less official/loosely worded requirements were used
- No requirements were discussed other than that the product needs to do its main function

What types of requirements were included? (Example: vacuum cleaner requirements)
Pick all that apply.

- Functional (The product shall vacuum up dust.)
- Performance (The product shall vacuum up dust < 1mm in diameter)
- Interface (The interface between the vacuum tube and the body will be 3 inches in diameter)
- Maintainability (The product should allow users to replace vacuum bags in less than 30 seconds)
- Reliability (The product shall last for 3 years without new parts needed)

If no design requirements were made during concept development, how were the users needs quantifiably turned into design concepts?

How important is defining requirements to your desired outcome?

- 1 - Not at all important
- 2 - Somewhat important
- 3 - Important
- 4 - Very important
- 5 - Extremely important

How satisfied are you tools and processes available for requirement creation?

- 1 - Not at all satisfied
- 2 - Somewhat satisfied
- 3 - Satisfied
- 4 - Very satisfied
- 5 - Extremely satisfied

Select any activities you participated in (Pick all that apply):

- Prepared metrics based on customer needs
- Collected benchmarking information
- Set ideal and marginally acceptable target values
- None of the above

If you could go back and do things differently as a designer or manager, would you spend more or less time on the requirements creation? Do you think any of requirements making process could be sped up? If so, how?

Section 4: MODELING

Section 4: MODELING

Was an analytical model of the product developed?

- Yes
- Yes, not completed
- No

Approximately how many months after incorporation was the analytical model started?

Approximately how long before it began producing results?

How many people worked on it?

How important is analytical modeling to your desired outcome?

- 1 - Not at all important
- 2 - Somewhat important
- 3 - Important
- 4 - Very important
- 5 - Extremely important

How satisfied are you with the tools and processes available for analytical modeling?

- 1 - Not at all satisfied
- 2 - Somewhat satisfied
- 3 - Satisfied
- 4 - Very satisifed
- 5 - Extremely satisfied

Was a computational model of the product developed?

- Yes, completed
- Yes, not completed
- No

Approximately how many months after incorporation was the computational model started?

Approximately how long did it take to make the computational model before the model began producing results?

What modeling software did you use?

How many people worked on the model? (please read the above part)

What was the main modeler's experience with the software used for the simulation?

- Complete Novice

- Took one class, but forgot most of it
- Used for some previous work, amateur
- Fluent
- Expert

Do you still use the model?

- Yes
- No
- Only very rarely (1-2 times a year for something small)

Approximately what month was the model no longer used (except for rare use)?

How important is computational modeling to your desired outcome?

- 1 - Not at all important
- 2 - Somewhat important
- 3 - Important
- 4 - Very important
- 5 - Extremely important

How satisfied are you with the tools and processes available for computational modeling?

- 1 - Not at all satisfied
- 2 - Somewhat satisfied
- 3 - Satisfied
- 4 - Very satisfied
- 5 - Extremely satisfied

How much do you think the technical modeling negatively affected the time line?

- A great deal
- A lot
- A moderate amount
- A little
- None at all

Was a cost model of the product made?

- Yes, completed
- Yes, not completed
- No

How many months after incorporation was cost modeling started?

How many people worked on the cost model?

Is the cost model still used? If no t, when was it no longer used?

How important was cost modeling to your desired outcome?

- 1 - Not at all important
- 2 - Somewhat important
- 3 - Important
- 4 - Very important
- 5 - Extremely important

How satisfied are you with the tools and processes available to do cost modeling?

- 1 - Not at all satisfied
- 2 - Somewhat satisfied
- 3 - Satisfied
- 4 - Very satisfied
- 5 - Extremely satisfied

What would you do differently about any of the modeling? Were any major improvements or mistakes made? Do you think any of these tasks could be sped up?

Section 5: CONCEPT GENERATION and SELECTION

Section 5: CONCEPT GENERATION and SELECTION

How many concept generation phases have you gone through?

1 - When was this concept generation phase started?

1 - How long did this concept generation last?

1 - How many individual concepts were created and chosen from?

1 - How long did the design team pursue more than one individual concept?

2 - When was this concept generation phase started?

2 - How long did this concept generation last?

2 - How many individual concepts were created and chosen from?

2 - How long did the design team pursue more than one individual concept?

3 - When was this concept generation phase started?

3 - How long did this concept generation last?

3 - How many individual concepts were created and chosen from?

3 - How long did the design team pursue more than one individual concept?

In general during concept generation phases:

How many people worked on concept generation?

Do you think designs were killed off too quickly?

- Yes
- No

Do you think designs were pursued too long?

- Yes
- No

Any elaboration on concept generation:

How important is concept generation to you desired outcome?

- 1 - Not at all important
- 2 - Somewhat important
- 3 - Important
- 4 - Very important
- 5 - Extremely important

How satisfied are you with the tools and processes available for concept generation?

- 1 - Not at all satisfied
- 2 - Somewhat satisfied
- 3 - Satisfied
- 4 - Very satisfied
- 5 - Extremely satisfied

What concept selection method was used?

- External decision
- Product champion
- Intuition
- Voting
- Web-based survey
- Pros and cons
- Prototype and test
- Decision matrices
- Other

When was concept selection started?

How long did concept selection last?

How many people worked on concept selection?

If you could go back and do things differently as a designer or manager, would you spend more or less time on the concept generation and selection? Do you think any of these activities could be sped up? If so, how?

Section 6: COMPLEXITY

Will this product be exposed to the outdoors regularly?

- Yes
- No

What environmental conditions are you designing for? What are the extremes?

How many individual, unique parts are required to make this product?

How many custom parts are needed to create this product?

How many off the shelf parts are needed to create this product?

For how many parts did you outsource the build?

(You created the design and gave the drawings/specifications to a hired company to build and deliver.)

For how many parts did you outsource the design?

(You hired company to design, build and deliver with only information about the function and interface requirements)

What did you outsource and what was the reasoning?

How important was outsourcing to your desire outcome?

- 1 - Not at all important
- 2 - Somewhat Important
- 3 - Important
- 4 - Very Important
- 5 - Extremely Important

How satisfied are you with the tools and processes available for outsourcing?

- 1 - Not at all satisfied
- 2 - Somewhat satisfied
- 3 - Satisfied
- 4 - Very satisfied
- 5 - Extremely satisfied

What is the communication ability of the product?

- WiFi
- Cellular
- Bluetooth
- On-grid
- Radio
- Microwave
- RFID
- Other
- None

How many defined interfaces are there in this product?

How many individual actions must be taken to assemble the product?

Individual action: completes one task (one solder, one tightening of a screw, etc.)

How many individual tools are needed to create this product?

How many of these tools must be significantly altered to manufacture this product?

What different fields of engineering or science are involved?

- Mechanical Engineering

- ☐ Electrical Engineering
- ☐ Biochemistry
- ☐ Physics
- ☐ Mathematics
- ☐ Computer Science
- ☐ Material Science
- ☐ Chemical Engineering
- ☐ Industrial Engineering
- ☐ Biology
- ☐ Chemistry
- ☐ Computer Science
- ☐ Other?

Other:

How many functions is the object intended to perform?

Please list these functions.

Does the product have onboard logic?

How many lines of code are used for the onboard logic?

Was a "technology readiness level" (TRL) used for understanding how far along the development timeline each prototype was?

- Yes
- Yes, but not called a TRL
- No

What TRL are you currently at?

If you could do it again would you do any of the design/build differently? Would you have outsourced less or more? What could have made things go faster?

Section 7: PROTOTYPING

Section 7: PROTOTYPING

How many iterations or iteration "sequences" have been done on the whole product to date?

Section 7A: PROTOTYPE ITERATION LOOPS

Section 7B: PROTOTYPING ITERATION LOOP

Name this prototype:

What was the main objective for this prototype?

How many months after incorporation was this prototype started?

How long did it take to complete this prototype?

How many employees worked on this prototype?

How important is the speed of this iteration to your desired outcome?

- 1 - Not at all important
- 2 - Somewhat important
- 3 - Important
- 4 - Very Important
- 5 - Extremely important

How satisfied are you with the tools and processes available to complete this iterate quickly?

- 1 - Not at all satisfied
- 2 - Somewhat satisfied
- 3 - Satisfied
- 4 - Very satisfied
- 5 - Extremely satisfied

Was this prototype tested on sample customers?

- Yes
- No

How was this prototype concept communicated to the audience?

- Verbal description
- Sketch
- Photos/Renderings
- Storyboard
- Video
- Simulation
- Interactive Media
- Physical Appearance Models
- Working Prototypes
- Other

Other:

What techincal testing was done on the product?

- Yes
- No
- Planned

What kind of testing?

How long did technical testing take?

In hindsight, would you spend more or less time on this prototype? What would you change? What could have been faster?

Was it determined that another prototype iteration was needed before market launch?

- Yes
- No

Section 7B: PILOTS

Have you done a pilot?

- Yes
- No
- Planning

How many pilots have you done? Can you please talk me through them?

How many more iterations do you think you need until you can pilot?

How many more iterations do you think you need until full market launch?

Section 8: MANUFACTURING

What is the plan for manufacturing? (Build your own manufacturing line, outsource some of it, etc.)

What part of the world do you plan to manufacture in?

When did you first discuss manufacturing?

Did you explicitly use design for manufacturing?

- Yes
- No
- Used some principles

When and how did you incorporate these above ideas?

What is your plan for manufacturing? (for example: build your own plant, sell to or partner with an established company, use a contract manufacturer, etc.)

Have you thought about standards and certification for your product? (Pick all that apply.)

- ☐ For safety
- ☐ For quality
- ☐ For reliability
- ☐ none
- ☐ other

When did you first discuss standards for your product?

What processes are necessary for manufacturing and assembling your product? Which have been the most difficult?

How important is scaling up your product to your desired outcome?

- ○ Not important at all
- ○ somewhat important
- ○ important
- ○ very important
- ○ extremely important

How satisfied are you with the tools and processes available for scaling up your product?

- ○ Not at all satisfied
- ○ somewhat satisfied
- ○ satisfied
- ○ very satisfied

- extremely satisfied

In hindsight, would you have manufactured any differently? Would you have considered standards differently? What would have made things go faster?

Section 9: OVERVIEW

Section 8: DESIGN OVERVIEW

Has your company been pressured by funding sources to speed up design due to slow development timelines vs. short investor timelines?

- Yes, all the time
- Yes, but not unreasonably
- Somewhat
- Not really, we don't feel pressured to rush
- No, they give us all the time we need

As a designer or manager, which of the steps discussed above slowed you down the most?
Pick all that apply.

- Targeting a market segment
- Gather user preferences
- Defining requirements
- Analytical Modeling
- Computational Modeling
- Cost Modeling
- Concept generation
- Concept selection

- ☐ Prototyping
- ☐ Customer testing of prototype
- ☐ Technical testing of prototype
- ☐ Other

As a designer or manager, which of the steps discussed above do you think could realistically be made faster?
Pick all that apply.

- ☐ Targeting a market segment
- ☐ Gather user preferences
- ☐ Defining requirements for product
- ☐ Analytical modeling
- ☐ Computational modeling
- ☐ Cost modeling
- ☐ Concept generation
- ☐ Concept selection
- ☐ Prototyping
- ☐ Customer testing of prototype
- ☐ Technical testing of prototype
- ☐ Other

Given hindsight, what would you have changed in how you approached the design process to shorten the development timelines? What kind of strategies would you try to implement?

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Bibliography

[1] Next Generation Cleantech. *Cleantech Group*, 2018.

[2] S.J. Ahmad, N. O'Regan, and A. Ghobadian. Leadership, decision making and internal stakeholder engagement. *International Journal of Management and Decision Making*, 6(3):345, 2005.

[3] Jorge Alcaide-Marzal, Jose Antonio Diego-Mas, and Gonzalo Acosta-Zazueta. product design. *Design Studies*, 66:144–176, 2020.

[4] M. Alonso-Abella, M. Chenlo, G. Nofuentes, and M. Torres-Ramirez. Analysis of spectral effects on the energy yield of different PV (photovoltaic) technologies: the case of four specific sites. *Energy*, 67:435–443, 2014.

[5] Robert A. and Phillips. Stakeholder Theory and A Principle of Fairness. *Business Ethics Quarterly*, 7(1):51–66, 1997.

[6] A. Arundel, R. Kemp, and T. Machiba. Measuring Eco-Innovation: Existing methods for macro-level analysis, in: Eco-Innovation in Industry: Enabling Green Growth. *OECD*, 2009.

[7] Standard Tables for Reference Solar Spectral Irradiances, Standard G173-03e. *American Society for Testing and Materials*, 2006.

[8] Silvia Ayuso, Miguel Ángel Rodríguez, Roberto García-Castro, and Miguel Ángel Ariño. Does stakeholder engagement promote sustainable innovation orientation? *Industrial Management and Data Systems*, 111(9):1399–1417, 2011.

[9] Hamdi Bashir and Vincent James Thomson. Estimating Design Complexity. *Journal of Engineering Design*, 10(3):247–257, 1999.

[10] Marcelo Bernal, John R Haymaker, and Charles Eastman. On the role of computational support for designers in action. *Design Studies*, 41:163–182, 2015.

[11] David Biello. Sunshine is free, so can photovoltaics be cheap? *Scientific American*, 2010.

[12] Faith Birol. World Energy Outlook. *International Energy Agency*, 2018.

[13] Steve Blank. Why the Lean Startup Changes Everything. In *On Entrepreneurship and Startups, HBR's 10 Must Reads*, pages 35–48. Harvad Business Review Press, Boston, 2013.

[14] Keith Bradsher. Solar Panel Maker Moves Work to China. *New York Times*, 2011.

[15] Riley E Brandt, C Rachel, Vera Steinmann, Daniil Kitchaev, Chris Roat, Sergiu Levcenco, Gerbrand Ceder, Thomas Unold, and Tonio Buonassisi. Rapid Photovoltaic Device Characterization through Bayesian Parameter Estimation Rapid Photovoltaic Device Characterization through Bayesian Parameter Estimation. *Joule*, 1(4):843–856, 2017.

[16] P. Brown. U.S. Solar Projects: DOE Section 1705 Guarantees. *Congressional Research Service*, 2011.

[17] Douglass Bryden. CAD and Rapid Prototyping for Product Design, 2014.

[18] A. Bumpus, J. Tansey, B. Luis, P. Henriquez, and C. Okereke. *Carbon Governance, Climate Change and Business Transformation.* Routledge, 2015.

[19] T. Buonassisi. Accelerating Materials Development with Machine Learning, Automation, and Computing. *LinkedIn*, 2019.

[20] Patrick Burtis. Creating the California Cleantech Cluster. *National Resources Defense Council, Environmental Entrepreneurs*, 2004.

[21] Center for Advanced Electronics Through Machine Learning (CAEML). *NSF Industry/University Cooperative Research Center*, 2020.

[22] L. Caldas. Generation of energy-efficient architecture solutions applying GENE_ARCH: An evolution-based generative design system. *Advanced Engineering Information*, 22(1):59–70, 2008.

[23] Federico Caprotti. Protecting innovative niches in the green economy: investigating the rise and fall of Solyndra, 2005–2011. *GeoJournal*, 82(5):937–955, 2017.

[24] Jongmin Choi. The rise of 3D printing and the role of user firms in the U.S.: evidence from patent data. *Technology Analysis and Strategic Management*, 30(10):1195–1209, 2018.

[25] Engineering Accreditation Commission. Criteria for Acceditating Engineering Programs, 2019.

[26] Juan Pablo Correa-Baena, Kedar Hippalgaonkar, Jeroen van Duren, Shaffiq Jaffer, Vijay R. Chandrasekhar, Vladan Stevanovic, Cyrus Wadia, Supratik Guha, and Tonio Buonassisi. Accelerating Materials Development via Automation, Machine Learning, and High-Performance Computing. *Joule*, 2(8):1410–1420, 2018.

[27] Josue R. Crespo-Varela, Gül E.Okudan Kremer, Conrad S. Tucker, and Lourdes A. Medina. An analysis of complexity measures for product design and development. *Proceedings of the ASME Design Engineering Technical Conference*, 3(PARTS A AND B):523–532, 2012.

[28] Anna R. Davies. Cleantech clusters: Transformational assemblages for a just, green economy or just business as usual? *Global Environmental Change*, 23(5):1285–1295, 2013.

[29] Olivier de Weck. Fundamentals of Systems Engineering. *MIT Course, Session 2: Requirements Definition*, 2015.

[30] Neal Dikeman. "What is Cleantech?". *Cleantech.Org*, 2018.

[31] Daniela Dirnberger, Gina Blackburn, Björn Müller, and Christian Reise. On the impact of solar spectral irradiance on the yield of different PV technologies. *Solar Energy Materials and Solar Cells*, 132:431–442, 2014.

[32] Qiuping Du and Aida Kadyova. *Stakeholder Engagement and Start-up Company Growth*. UmeaSchool of Business and Economics, 2015.

[33] O. Dupre, R. Vaillon, and M.A. Green. Thermal behavior of photovoltaic devices: physics and engineering. *Solar Energy Materials & Solar Cells*, 140:92–100, 2015.

[34] C. Eastman, R. Sacks, and G. Lee. Development of a knowledge-rich CAD system for American precast concrete industry. *Association for CAD in Architecture*, 2003.

[35] Jessica Eid, Haifan Liang, Issam Gereige, Sang Lee, and Jeroen Van Duren. Combinatorial study of NaF addition in CIGSe films for high efficiency solar cells. *Progress in Photovoltaics: Research and Applications*, 23:269–280, 2015.

[36] Juliet Eilperin. Why the Clean Tech Boom Went Bust. *Wired*, 2012.

[37] Steven D. Eppinger and Tyson R. Browning. *Design Structure Matrix Methods and Applications.* MIT Press, 2012.

[38] P. Faine, Sarah R. Kurtz, C. Riordan, and J. M. Olson. The influence of spectral solar irradiance variations on the performance of selected single-junction and multijunction solar cells. *Solar Cells*, 31(3):259–278, 1991.

[39] Fehrenbacher. "Why the Solyndra mistake is still important to remember". *Fortune*, 2015.

[40] John Fialka. Why China Is Dominating the Solar Industry. *Scientfic American*, 2016.

[41] PlantPredict, version 8. `https://plantpredict.com/`, year = 2020.

[42] First Solar Series 4 PV Module. `http://www.firstsolar.com/-/media/First-Solar/Technical-Documents/Series-4-Datasheets/Series-4V2-Datasheet.ashx`, 2015.

[43] E. Fitzgerald, A. Wankerl, and C. Schramm. *Inside Real Innovation: How the Right Approach Can Move Ideas from R&D to Market - And Get the Economy Moving.* 2013.

[44] Tom Forester. *The Information Technology Revolution.* MIT Press, 1985.

[45] Edward Freeman. *Strategic Mangaement: A Stakeholder Approach.* Social Science Research Network Electronic Paper Collection, Boston, 1984.

[46] R. Edward Freeman, Kirsten Martin, and Bidhan Parmar. Stakeholder capitalism. *Journal of Business Ethics*, 74(4):303–314, 2007.

[47] Autodesk. `https://www.autodesk.com/solutions/generative-design`, 2020.

[48] Benjamin Gaddy, Varun Sivaram, and Francis O'Sullivan. Venture capital and cleantech: The wrong model for clean energy innovation. *MIT Energy Initiative Working Paper*, 2016.

[49] GCCA. GCCA - Making Local Global. *globalcleantech.org*, 2019.

[50] Lucien Georgeson, Federico Caprotti, and Ian Bailey. 'It's all a question of business': Investment identities, networks and decision-making in the cleantech economy. *Geografiska Annaler, Series B: Human Geography*, 96(3):217–229, 2014.

[51] Shikhar Ghosh and Ramana Nanda. Venture Capital Investment in the Clean Energy Sector. *SSRN Electronic Journal*, 2012.

[52] G. R. Gibbs. Chapter 4: Thematic Coding and Categorizing. *Analyzing Qualitative Data*, 2007.

[53] Francis J. Gouillart. The race to implement co-creation of value with stakeholders: Five approaches to competitive advantage. *Strategy and Leadership*, 42(1):2–8, 2014.

[54] M.A. Green. General temperature dependence of solar cell performance and implications for device modelling. *Progress in Photovoltaics: Research and Applications*, 11:333–340, 2003.

[55] Christian A. Gueymard. SMARTS2: a simple model of the atmospheric radiative transfer of sunshine: algorithms and performance assessment. *Report No. FSEC-PF-270-95*, pages 1–84, 1995.

[56] Christian A. Gueymard. Parameterized transmittance model for direct beam and circumsolar spectral irradiance. *Solar Energy*, 71(5):325–346, 2001.

[57] Christian A. Gueymard. The sun's total and spectral irradiance for solar energy applications and solar radiation models. *Solar Energy*, 76(4):423–453, 2004.

[58] C. Haeuselmann and N. Harjula. The meta-cluster GCCA is shedding light on the life of th world's cleantch clusters. *Presentaitontto European Cleantech Cluster Forum*, 2013.

[59] J.R. Hauser and D. Clausing. The House of Quality. *Harvard Business Review*, 1988.

[60] S. Hegedus. Review of photovoltaic module energy yield (kWh/kW): comparison of crystalline Si and thin film technologies. *Energy Environ. Sci.*, 2:218–233, 2011.

[61] Joshua P. Howe. *Making Climate Change History : Documents From Global Warming's Past*. eBook Collection EBSCOhost, 2017.

[62] L. Huaccho Huatuco, J. Efstathiou, S. Sivadasan, and A. Calinescu. A Model for the Control of Complexity in Manufacturing Systems. *IFAC Proceedings Volumes*, 34(17):123–128, 2001.

[63] Thomas Huld and Ana M. Gracia Amillo. Estimating PV module performance over large geographical regions: The role of irradiance, air temperature, wind speed and solar spectrum. *Energies*, 8(6):5159–5181, 2015.

[64] Hulstrom, Boyd, and Riordan. No Title. *Solar Cells*, 15:365–391, 1985.

[65] M. Iwabu. What complicated B2B design? *Medium*, 2018.

[66] Ryan Jacobs, Tam Mayeshiba, A Ben, Luke Miles, Max Williams, Matthew Turner, Raphael Finkel, and Dane Morgan. The Materials Simulation Toolkit for Machine learning (MAST-ML): An automated open source toolkit to accelerate data-driven materials research. *Computational Materials Science*, 176, 2020.

[67] Adam Jaffe, Richard Newell, and Robert Stavins. Technological change and the environment. *Handbook of Environmental Economics*, 1, 2003.

[68] Arnulf Jäger-Waldau. Snapshot of photovoltaics—February 2019. *Energies*, 12(5), 2019.

[69] A. Jain, S.P. Ong, G. Hautier, W. Chen, W.D. Richards, S. Dacek, S. Cholia, D. Gunter, D. Skinner, G. Ceder, and K.A. Persson. The Materials Project: A materials genome approach to accelerating materials innovation. *APL Materials*, 1(1), 2013.

[70] Patrick Janssen. Dexen : A scalable and extensible platform for experimenting with population-based design exploration algorithms. *Artifical intelligence for engineering design analysis and manufacturing*, pages 443–455, 2015.

[71] Christian N. Jardine, T.R. Betts, R. Gottschalg, D.G. Infield, and Kevin Lane. Influence of Spectral Effects on the Performance of Multijunction Amorphous. *Proc of PV in Europe - From PV Technology to Energy Solutions*, pages 2–5, 2002.

[72] M. K. Jeon, J. Cooper, and P. McGinn. Investigation of PtCoCr/C catalysts for methanol electro-oxidation identified by a thin film combinatorial method. *Journal of Power Sources*, 192(2):391–395, 2009.

[73] R. Johnston. Keepin ' it Clean (tech) Assessing South Africa ' s cleantech ecosystem to improve a framework for Cleantech Innovation and Entrepreneurship Ecosystems in Developing Countries Rheanna Johnston Supervisor :. 2019.

[74] N. Johnstone. Environmental Policy, Technological Innovation and Patents. *OECD Studies on Environmental Innovation*, 2008.

[75] Y.E. Kalay. Modeling objects and environments. *Wiley*, 1989.

[76] M. Kato, T. Fujiseki, T. Miyadera, and H. Fuyiwara. Universal rules for the visible-light absorption in hybrid perovskite materials. *Journal of Applied Physics*, 121(11), 2016.

[77] Rubaiat Habib Kazi, Tovi Grossman, Hyunmin Cheong, Ali Hashemi, and George Fitzmaurice. *DreamSketch : Early Stage 3D Design Explorations with Sketching and Generative Design*. 2017.

[78] Mike Keating. Measuring design quality by measuring design complexity. *Quality Electronic Design*, 2000.

[79] Kebotix. Enabling a new age of discovery. 2020.

[80] Shahroz Khan, Erkan Gunpinar, and Bekir Sener. GenYacht: An interactive generative design system for computer-aided yacht hull design. *Ocean Engineering*, 191(August):106462, 2019.

[81] Shahroz Khan and Muhammad Junaid. A Generative Design Technique for Exploring Shape Variations.

[82] T. Kollman and A. Kuckertz. nture Capital Investors' Communicative Needs. *International Journal of Technology Management*, 34(1):47–62, 2006.

[83] Janet L Kolodner. An Introduction to Case-Based Reasoning. 1992.

[84] Sivam Krish. Computer-Aided Design A practical generative design method. *Computer-Aided Design*, 43(1):88–100, 2011.

[85] Rachel C Kurchin, Jeremy R Poindexter, V Ville, Hele Savin, and Carlos Ca. How much physics is in a current-voltage curve? Inferring defect properties from photovoltaic device measurements. pages 1–20.

[86] Rachel Chava Kurchin. Computational frameworks to enable accelerated development of defect-tolerant photovoltaic materials. 2019.

[87] A.G. Kusne, T. Gao, A. Mehta, L. Ke, M.C. Nguyen, K.-M. Ho, V. Antropov, C.-Z. Wang, M.J. Kramer, C. Long, and I. Takeuchi. On-the-fly machine-learning for high-throughput experiments: search for rare-earth-free permanent magnets. *Sci. Rep.*, 4(6367), 2014.

[88] Martin LaMonica. Harsh lessons from Evergreen Solar flame-out. *Cnet*, 2011.

[89] Adam Lashinsky. First Solar Rises Again. *Fortune*, 2017.

[90] Mitchell Lee and Alex Panchula. Spectral correction for photovoltaic module performance based on air mass and precipitable water. *Conference Record of the IEEE Photovoltaic Specialists Conference*, 2016-Novem:1351–1356, 2016.

[91] Jay Levy. Investor Relations for Startups. *Zelkova Ventures*, 2017.

[92] Udo Lindemann, Maik Maurer, and Thomas Braun. *Structural Complexity Management: An Approach for the Field of Product Design - Udo Lindemann, Maik Maurer, Thomas Braun - Google Books*. 2009.

[93] Haohui Liu, Armin G. Aberle, Tonio Buonassisi, and Ian Marius Peters. On the methodology of energy yield assessment for one-Sun tandem solar cells. *Solar Energy*, 135:598–604, 2016.

[94] Macrotrends LLC. Natural gas prices - historical chart. *https://www.macrotrends.net/2478/natural-gas-prices-historical-chart*, 2020.

[95] Stuart P. Lloyd. Least Squares Quantization in PCM. *IEEE Transactions on Information Theory*, 28(2):129–137, 1982.

[96] Max Lyadvinsky. Startups Need More Than Money to Succeed – They Need Smart Money. *Entrepreneur*, 2018.

[97] M.L. Maher and P. Pu. *Issues and Applications of Case Based Reasoning to Design*. 1997.

[98] M.L. Maher and P. Pu. Issues and applications of case-based reasoning to design. *Psychology Press*, 2014.

[99] B Marion, B Kroposki, K Emery, D Myers, J del Cueto, and C Osterwald. Validation of a Photovoltaic Module Energy Ratings Procedure at NREL. *NREL*, 1999.

[100] Richard Martin. Exxon Has a Clever Way to Capture Carbon - If It Works. *MIT Technology Review*, 2016.

[101] Justin Matejka, Michael Glueck, Erin Bradner, Ali Hashemi, Tovi Grossman, and George Fitzmaurice. Dream Lens : Exploration and Visualization of Large-Scale Generative Design Datasets. 2018.

[102] Scott McGrew. "Solyndra to Declare Bankruptcy". *NBC Bay Area*, 2011.

[103] Paulo Luzio De Melo, Miguel Tavares, Jorge Martins, and Dava Newman. A Microcontroller Platform for the Rapid Prototyping of Functional Electrical Stimulation-Based Gait Neuroprostheses. 2015.

[104] Andre Mermoud. PVSyst Photovoltaic Software, 2020.

[105] Moriah Meyskens and Alan L. Carsrud. Nascent green-technology ventures: A study assessing the role of partnership diversity in firm success. *Small Business Economics*, 40(3):739–759, 2013.

[106] Michael Migendt. *Accelerating Green Innovation: Essays on Alternative Investments in Clean Technologies*. Springer Gabler, 2017.

[107] Michael Migendt, Friedemann Polzin, Florian Schock, Florian A. Täube, and Paschen von Flotow. Beyond venture capital: An exploratory study of the finance-innovation-policy nexus in cleantech. *Industrial and Corporate Change*, 26(6):973–996, 2017.

[108] Sunghyun Moon. Highly efficient single-junction GaAs thin-film solar cell on flexible substrate. *Scientific Reports*, 6, 2016.

[109] S. Mraz. Changes in the Engineering Profession over 80 years. *MachineDesign*, 2009.

[110] L. Nelson, M. Fritchtl, and A. Panchula. Changes in Cadmium Telluride Photovoltaic System Performance due to Spectrum. *IEEE Journal of Photovoltaics*, 3(1):488–493, 2013.

[111] Larissa F Nietner. Signature redacted Signature redacted. 2017.

[112] G. Nofuentes, C. A. Gueymard, J. Aguilera, M. D. Pérez-Godoy, and F. Charte. Is the average photon energy a unique characteristic of the spectral distribution of global irradiance? *Solar Energy*, 149:32–43, 2017.

[113] Matthew Nordan. "The State of Cleantech Venture Capital, Part 1: The Money". *Secret Formula*, 2011.

[114] Sharon Novak and Steven D. Eppinger. Sourcing by design: Product complexity and the supply chain. *Management Science*, 47(1):189–204, 2001.

[115] Margaret P. O'Mara. *The code: Silicon Valley and the remaking of America*. Penguin Press, 2019.

[116] F. Oviedo, Zekun Ren, S. Shijing, C. Settens, L. Zhe, N.T.P. Hartono, S. Ramasamy, B. DeCost, S. Tian, G. Romano, A.G. Kusne, and T. Buonassisi. Fast and interpretable classificatino of small X-ray diffraction datasets using data augmentation and depp neural networks. *NPJ Computational Materials*, 5(1):1–9, 2019.

[117] L. Palinkas. Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Adm Policy Ment Health*, 42(5):533–544, 2015.

[118] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perro, and E. Duchesnay. Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[119] A T D Perera, P U Wickramasinghe, Vahid M Nik, Solar Energy, Ecole Polytechnique, Fédérale De Lausanne, and Ch Lausanne. Introducing reinforcement learning to the energy system design process. *Applied Energy*, 262(February):114580, 2020.

[120] I. Marius Peters. Global Comparison of the Impact of Temperature and Precipitable Water on CdTe and Silicon Solar Cells. *2017 IEEE 44th Photovoltaic Specialist Conference (PVSC)*, pages 1140–1142, 2017.

[121] Ian Marius Peters and Tonio Buonassisi. Energy Yield Limits for Single-Junction Solar Cells. *Joule*, 2(6):1160–1170, 2018.

[122] Ian Marius Peters and Tonio Buonassisi. Energy Yield Limits for Single-Junction Solar Cells. *Joule*, 2(6):1160–1170, 2018.

[123] Ian Marius Peters, Haohui Liu, Thomas Reindl, and Tonio Buonassisi. Global Prediction of Photovoltaic Field Performance Differences Using Open-Source Satellite Data. *Joule*, 2(2):307–322, 2018.

[124] Friedemann Polzin, Michael Migendt, Florian Taube, and Paschen von Flotow. Public Policy influence on renewable energy investments - A panel data study across OECD countries. *Energy Policy*, 80:98–111, 2015.

[125] Mauro Pravettoni, Anika Komlan, Roberto Galleano, Harald Müllejans, and Ewan D. Dunlop. An alternative method for spectral response measurements of large-area thin-film photovoltaic modules. *Progress in Photovoltaics: Research and Applications*, 20:416–422, 2012.

[126] Narahani Pujari. International Technology Roadmap for Photovoltaics. *ITRPV*, 2018.

[127] Venkat Ramaswamy, Kerimcan Ozcan, and Robert Randall. Strategy and co-creation thinking. *Strategy & Leadership*, 41(6):5–10, 2013.

[128] A. Rascouet. Total to Buy Battery Maker Saft in Push to Expand Clean Energy. *Bloomberg*, 2016.

[129] Eric Reis. *The Lean Startup: How Today's Entrepreneurs Use Continuous Innovation to Create Radically Successful Businesses*, volume 29. 2012.

[130] Nicholas Riedel, Santamaria Lancia, Adrian Alejo, Sune Thorsteinsson, and Peter Poulsen. Validation of the spectral mismatch correction factor using an LED-based solar simulator. *Paper presented at the 5th international workshop on LED and Solar Applications*, 2017.

[131] J. M. Ripalda, J. Buencuerpo, and I. García. Solar cell designs by maximizing energy production based on machine learning clustering of spectral variations. *Nature Communications*, 9(1):5126, 2018.

[132] AJ Rix, JDT Steyl, J. Rudman, U. Terblanche, and J.L. van Niekerk. First Solar's CdTe module technology - performance, life cycle, health and safety impact assessment. *Independent Review of Technology*, 2015.

[133] C.a Rodriguez-Toro, G Jared, and K Swift. Product - Development Complexity Metrics: a Framework for Proactive-Dfa Implementation. *Proceedings of DESIGN 2004, the 8th International Design Conference*, (April):483 – 490, 2004.

[134] R.G. Ross. Interface Design Considerations for Terrestrial Solar Cell Modules. *Jet Propulsion Laboratory*, pages 801–806, 1976.

[135] Ranjana Roy, R. Evans, M.J. Low, and D.K. Williams. Addressing the impact of high levels of product variety on complexity in design and manufacture. *Journal of Engineering Manufacture*, 225(10):1939–1950, 2011.

[136] R. Schmager, M. Langenhorst, J. Lehr, Uli Lemmer, B. Richards, and Ulrich Paetzold. Methodology of energy yield modelling of perovskite-based multijunction photovoltaics. *Optics Express*, 27:507–523, 2019.

[137] Steven E. Schoenherr. The Digital Revolution, 2004.

[138] G. Schuh and U. Schwenk. Produktkomplexität managen - Strategien, Methoden, Tools.

[139] Ikhlaq Sidhu, Shomit Ghose, and Paul Nerger. Solyndra 2011 Case Study. 2012.

[140] J. Simpson. Oxford English Dictionary Online. 2020.

[141] P. Singh and N.M. Ravindra. Temperature dependence of solar cell performance—an analysis. *Solar Energy Materials & Solar Cells*, 101:36–45, 2012.

[142] P. Srivastava and N. Hopwood. A Practical Iterative Framework for Qualitative Data Analysis. *International Journl of Qualitativce Methods*, 2009.

[143] N. Strevel, L. Trippel, and M. Gloeckler. Performance characterization and superior energy yield of First Solar PV power plants in high temperature conditions. *Photovoltaics International*, 17(148-154).

[144] Nam P. Suh. Complexity in engineering. *CIRP Annals - Manufacturing Technology*, 54(2):46–63, 2005.

[145] Victor Tang and Vesa Salminen. Towards a theory of complicatedness: framework for complex systems analysis and design. *Complexity*, (August), 2001.

[146] N.K. Taylor. An Expert System to Assist in Design. *Thesis, University of Nottingham*, 1990.

[147] Neil Thompson and Jennifer Ballen. First Solar. pages 1–33, 2017.

[148] R. Trieu. In Case You Missed 'Em: 6 Examples of Generative Design in Manufacturing. *Redshift by Autodesk*, 2019.

[149] The Honey Module: DataSheet, 2015.

[150] Masaki Tsuji, Md Mijanur Rahman, Yoshihiro Hishikawa, Kensuke Nishioka, and Takashi Minemoto. Uniqueness verification of solar spectrum obtained from three sites in Japan based on similar index of average photon energy. *Solar Energy*, 173(July):89–96, 2018.

[151] Y. Tsuno, Y. Hishikawa, and K. Kurokawa. A method for spectral response measurements of various PV modules. Technical report, Valencia, Spain, 2008.

[152] M. Turrin, P. Von Buelow, and R. Stouffs. Design explorations of performance driven geometry in architectural design using parametric modeling and genetic algorithms. *Advanced Engineering Information*, 25(4):656–675, 2011.

[153] Karl Ulrich and Steven Eppinger. *Product Design and Development*. 2015.

[154] A. Ulwick. What customers want. 2005.

[155] A. Ulwick. Jobs to be Done: Theory to Practice. 2016.

[156] Alain Verbeke and Vincent Tung. The Future of Stakeholder Management Theory: A Temporal Perspective. *Journal of Business Ethics*, 112(3):529–543, 2013.

[157] Reinhilde Veugelers. Which policy instruments to induce clean innovating? *Research Policy*, 41(10):1770–1778, 2012.

[158] Edward Welles. Going for Broke. *Archive at the Wayback Machine*, 1998.

[159] A. Westrenius and L. Barnes. Managing Complex Business Relationships: Small Business and Stakeholder Salience. *The Journal of Developing Areas*, 49(6), 2015.

[160] By Rita White. Leveraging automation as a strategy to overcome today ' s laboratory challenges. pages 24–25, 2019.

[161] Stefan Wilbert, Wilko Jessen, C. Gueymard, Jesús Polo, Zeqiang Bian, Anton Driesse, Aron Habte, Aitor Marzo, Peter Armstrong, Frank Vignola, and Lourdes Ramírez. Proposal and Evaluation of Subordinate Standard Solar Irradiance Spectra. *ISES Solar World Congress 2015*, 2017.

[162] S R Williams, T R Betts, T Helf, R Gottschalg, H G Beyer, and D G Infield. Modelling Long-Term Module Performance Based On Realistic Reporting Conditions With Consideration to Spectral Effects. *Proceedings of the 3rd World Conference on Photovoltaic Energy Conversion, Osaka*, pages 1908–1911, 2003.

[163] D.I. Wimpenny, P.M. Pandey, and L.J. Kumar. volume 21. 1999.

[164] Philip Wolfe. *The solar generation: childhood and adolescence of terrestrial photovoltaics*. Wiley, 2018.

[165] R. Wuerz, W. Hempel, and P. Jackson. Diffusion of Rb in polycrystalline Cu(In,Ga)Se 2 layers and effect of Rb on solar cell parameters of Cu(In,Ga)Se 2 thin-film solar cells. *Journal of Applied Physics*, 124(16), 2018.

[166] X. Xie, S. Guevara, R. Johnston, and J. Wylie. Assessing Cleantech Innovation and Entrepreneurship Ecosystems in Developing Countries. *Client Report for UNIDO-GCIP*, 2019.

[167] Yamaha Motor Launches Modular Z:TA-R YSM40R Surface Mounter, Ultra-High-Speed Rotary Head Achieves World-Leading 200,000 CPH, 2016.

[168] L. Zaman, W. Stuerzlinger, and C. Neugebauer. MACE: A new interface for comparing and editing of multiple alternative documents for generative design. *Proceeding of the 2017 ACM Symposium on Document Engineering*, pages 67–76, 2017.

[169] L. Zaman, W. Stuerzlinger, C. Neugebauer, R. Woodbury, M. Elkhaldi, N. Shireen, and M. Terry. Gem-ni: A system for creating and managing alternatives in generative design. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 1201–1210, 2015.

[170] A. Zunger. Inverse design in search of materials with target functionalities. *Nature Reviews Chemistry*, 2, 2018.