Prospective environmental analyses of emerging technology: A critique, a proposed methodology, and a case study on incremental sheet forming

Daniel R Cooper[a] and Timothy G Gutowski[b]

[1] University of Michigan, 2458 George G. Brown Laboratory, 2350 Hayward, Ann Arbor, MI, USA, 48109-2125

[2] Massachusetts Institute of Technology, 77 Massachusetts Avenue, Room 35-234, Cambridge, MA, USA, 02139

Abstract

Prospective environmental assessment of emerging technology is necessary in order to inform designers of beneficial changes early in a technology's development, and policy makers looking to fund projects and nudge manufacturers towards the most sustainable application of a technology. Existing analyses often have shortcomings such as failing to consider the environmental impacts in all stages of a product's lifecycle; implicitly assuming that the emerging technology will be cost effective wherever it is technically viable; and assuming optimistic application scenarios that discontinue long established trends in human behavior. In this article, we propose a new approach, complementary to the prospective and anticipatory Life Cycle Assessment (LCA) literature, addressing the above concerns and attempting to make sense of the large uncertainties inherent in such analyses by using distributions to model all the inputs. The paper focuses on emerging manufacturing technologies, such as incremental sheet forming (ISF), but the issues examined are also applicable to new end-use products, such as autonomous vehicles. This paper makes use of approaches (such as Bass modeling and product cannibalization considerations) familiar to those in the business community who anticipate market diffusion of a new technology and the effect on existing technology sales.

The proposed methodology is demonstrated by estimating the potential environmental impacts in the US car industry by 2030 of an emerging double-sided ISF process. Energy and cost models of ISF and drawing are used to estimate potential mean savings of around 100 $TJ_{primary}$ and 60 million USD per year by 2030.

Keywords: emerging technology, prospective environmental analysis, incremental sheet forming, anticipatory environmental analysis, industrial ecology, sustainable technology

Conflict of interest statement: The authors have no conflict to declare.

Address correspondence to: Daniel Cooper, University of Michigan, 2458 George G. Brown Laboratory, 2350 Hayward, Ann Arbor, MI, USA, 48109-2125. *Email:* drcooper@umich.com

<heading level 1> Introduction

There is an increasing focus in government, academia and business on the potential environmental impacts of new technologies. “How much energy will this save?” and “By how much will this cut greenhouse gas emissions?” are questions now routinely asked of researchers by funding bodies. “This” typically refers to a new product, such as autonomous vehicles, or a new manufacturing process, such as additive manufacturing (AM). Subsequently, analyses attempting to answer these questions are becoming common in government reports and academic papers. In the DOE *Quadrennial Technology Review* there is now a chapter dedicated to “Innovating Clean Technologies in Advanced Manufacturing” that highlights such work (US Department of Energy 2015); for example, Huang et al.'s (2015) study on future energy and emissions savings derived from the use of AM to make aircraft components. Such studies not only inform short term funding decisions but guide legislation; for example, the potential for energy efficient lighting to save energy at the national level forms a central thesis in the US *Energy Independence and Security Act* of 2007 (US Congress 2007) and the *American Recovery and Reinvestment Act* of 2009 (US Congress 2010). Given the potential influence of prospective assessments, there is a need for scrutiny of existing methodologies.

In recent years, there has been a proliferation of publications on the anticipated environmental benefits of emerging technologies. Table S1 of the supporting information available on the Journal’s website presents a representative sample. Some analyses consider the impacts in a single phase of the product’s life cycle (usually use phase); see, for example, Brodrick's (2010) predictions of US energy savings from the use of energy-efficient solid state lighting, or Levy et al.'s (2016) analysis on US energy savings and emissions reductions from increased insulation in new homes. Typically, however, the studies follow an extended life cycle assessment (LCA) methodology: the relative impacts of a new technology are calculated by comparing the cradle-to-grave LCA of an emerging technology to a base case scenario. These relative impacts are then translated into national level savings by scaling according to the national market size for the service being provided. This approach assumes that sufficient incentives exist for consumers or manufacturers to buy and use the technology. Few studies produce cost models that allow the new and existing technology to be compared in different applications (a notable exception is the above analysis by Brodrick). Without such models, researchers run the risk of implicitly assuming that a technology will be used wherever it is technically viable.

Previous work centered at the Technical University in Denmark (Bhander et al. 2003) and Arizona State University (Wender and Seager 2011; Wender et al. 2014a; Wender et al. 2014b; Wender et al. 2017) has seen concepts developed around *anticipatory/prospective LCAs* of individual products or technologies that include parameter uncertainty in the technology model, allowing feedback to the technology developers. Uncertainties are high in these assessments. As highlighted by Wender et al. (2014), current LCA practices often rely on point-value estimates for environmental impact intensities (e.g., CO_{2eq} per kg of material produced); whereas, often only the order of magnitude is known with confidence (Ashby 2012). In anticipatory LCA, these uncertainties are compounded by scenario and model uncertainty. In order to convey the uncertainty of the final results, the Arizona State authors present overlaid probability distributions corresponding to the likely impacts caused by the baseline and alternative technologies (Prado-Lopez et al. 2016). Anticipatory LCAs allow for one-to-one comparisons between an emerging and existing technology; however, the net industry level impacts of a new technology depend on the scale at which it is used, what it is used for, and whether or not it displaces the existing technology.

Existing studies implicitly assume that new technology displaces existing technology one-for-one; however, this assumption contradicts findings elsewhere in the literature. For example, Thomas (2003) models the rebound effect for reuse, finding that the only scenario in which reuse can fully replace new product sales is when the second-hand price is zero and the value customers place on the newness of the product is low; mutually exclusive conditions in most cases. Fremstad (2017) offers an alternative analysis, finding that Craigslist likely does reduce waste disposal in California and Florida. Elsewhere, there has been significant work in recent years on the displacement of primary material production because of recycling. Vadenbo et al. (2016) devise a reporting framework to allow transparent accounting of displacement potentials when evaluating resource recovery. Geyer et al. (2015) brand the assumption of a one-to-one displacement in recycling a "common misconception," and Zink et al. (2016) use partial equilibrium modeling to argue that one-to-one displacement is unlikely in commodity markets. The above studies are from the industrial ecology literature but there are analogous studies in the marketing literature (e.g., Mason and Milne 1994; Srinivasan et al. 2005) often written under the banner of 'product cannibalization.' The marketing literature implicitly encourages increased consumption because much of it is dedicated to how companies can avoid product cannibalization.

The improved performance (e.g., increased efficiency and lower price) of a new technology may lead to a rebound effect (Jevons 1866; Hertwich 2005), opening up new markets and increasing overall sales. For example, Tsao et al. (2010) demonstrate that improvements in lighting efficiency and performance have so far led to ever greater demands for lighting services, from electrification and near continuous lighting of homes and offices to megawatt LED screens in sports stadia. The historical trend highlighted by Tsao et al. does not invalidate the predictions of Brodrick and others, that assume one-to-one displacement of LED lighting for other technologies (e.g., fluorescent or incandescent lighting). However, it does suggest that researchers should consider that a long established socio-economic consumption trend could continue. The rebound effect is not limited to the consumption of direct energy. For example, Zink and Geyer (2017) describe how circular economy activities (reuse and recycling) can increase overall material production, offsetting any environmental benefits.

Even a successful, cost-effective technology will not achieve 100% market share instantaneously. It takes time for a technology to "diffuse," for the innovation to spread across markets over time (Chandrasekarn and Tellis 2007). Technology diffusion is often depicted as an S-curve: first, innovators use the technology; then, as time progresses the majority picks it up; and then finally laggards buy the technology, at which point it has saturated the market (Rogers 2003). A popular description is the Bass (1969) model (equation 1) which, with tuned coefficient values, has been found to fit data for most product introductions.

$$S(t)=\left(p+q\frac{F(t-1)}{m}\right)\times(m-F(t-1)) \quad (1)$$

Where S(t) is the predicted number of sales in year t, F(t) is the cumulative number of sales, p is the coefficient of innovation, q is the coefficient of imitation, m is the potential market size, and t is time measured in years. Few papers examining the environmental benefits of emerging technology consider technology diffusion. Notable exceptions include Das et al. (2016) who use an adoption scenario based on previous vehicle technology adoption rates in order to predict future energy savings from vehicle lightweighting.

<heading level 2> *Scope of current work*

The analysis presented in this article focuses on energy demand, which is typically a good indicator of other environmental impacts (Ashby 2012); however, stakeholders will often be concerned with multiple, potentially conflicting, criteria (e.g., energy efficiency and NOx emissions). Elsewhere, a host of literature is dedicated to evaluating tradeoffs and developing strategies for making optimal decisions when faced with conflicting objectives. Strategies include intuitive ranking plus documentation/review of the options defined in the Pareto set; reformulating an objective as a constraint; using penalty functions or weight factors in order to evaluate tradeoffs and find optimal solutions. Useful references for the reader include Keeney and Raiffa's (1993) book on preferences and value tradeoffs, and Michael Ashby's work on multi-objective optimization in material design and selection (Ashby 2000, 2011).

The *Proposed methodology* is demonstrated in *Potential impacts of a new manufacturing process* by considering a new double-sided incremental sheet forming (ISF) process (Figure 1). ISF is a dieless forming process: the sheet metal blank is clamped around the periphery, and CNC indenters trace out a tool path, progressively indenting the sheet and making a three dimensional part out of the flat blank (Hirt and Bambach 2012).

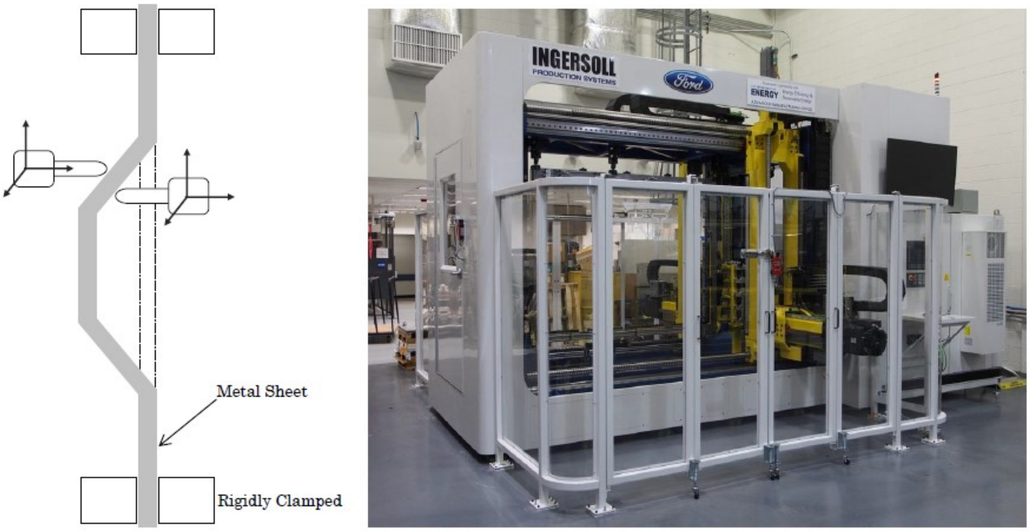


Figure 1: ISF process and machine

Double sided incremental sheet forming technology	**Specification**
Forming area (blank sizes)	Rectangular blanks with side lengths in 0.5 m increments up to 2.0x1.5 m
Forming depth	0.475 m
Tolerance	Bilateral profile tolerance of ±1 mm
Surface finish	Ra < 30 μm
Maximum tool speed	5 m per minute
Maximum wall angle	90 degrees
Production rate	0.1-1 parts hour^{-1} for sheet metal parts made by car companies
Tool lead time	0 days, with successfully formed parts produced first time

Table 1: Specifications for a new ISF process

Traditionally, car industry prototyping has used hydraulic stamping presses and part-specific cast and machined zinc drawing die-sets. ISF presents the opportunity to avoid the die-making process, saving time, money, and energy. However, since the earliest ISF processes were developed in the 1990s, ISF has seen limited industrial adoption because of slow forming times (Lamminen et al. 2004) and the poor dimensional accuracy of the formed part (Allwood et al. 2005). A recent US Department of Energy funded project has seen extensive research into overcoming the above issues and aims to achieve the specifications shown in Table 1.

<heading level 1> Proposed methodology

The industry level environmental impacts of a new technology depend on: (1) Technology level impacts and costs of the emerging technology compared to conventional technology (for manufacturing processes these would be calculated for a relevant functional unit, such as per part produced); (2) The effect on aggregate consumption due to the scale at which the emerging technology is used (e.g., annual production of parts).

Practitioners can use Figure 2 (which presents a flow chart of tasks and alternative tools for completing the tasks) in order to complete the proposed methodology. Multiple options are included in Figure 2 because the appropriate tool will depend on the technology, data availability, and the resources available to the researcher. The following sub-section is dedicated to handling the many uncertainties. Subsequently, each stage of the methodology is discussed.

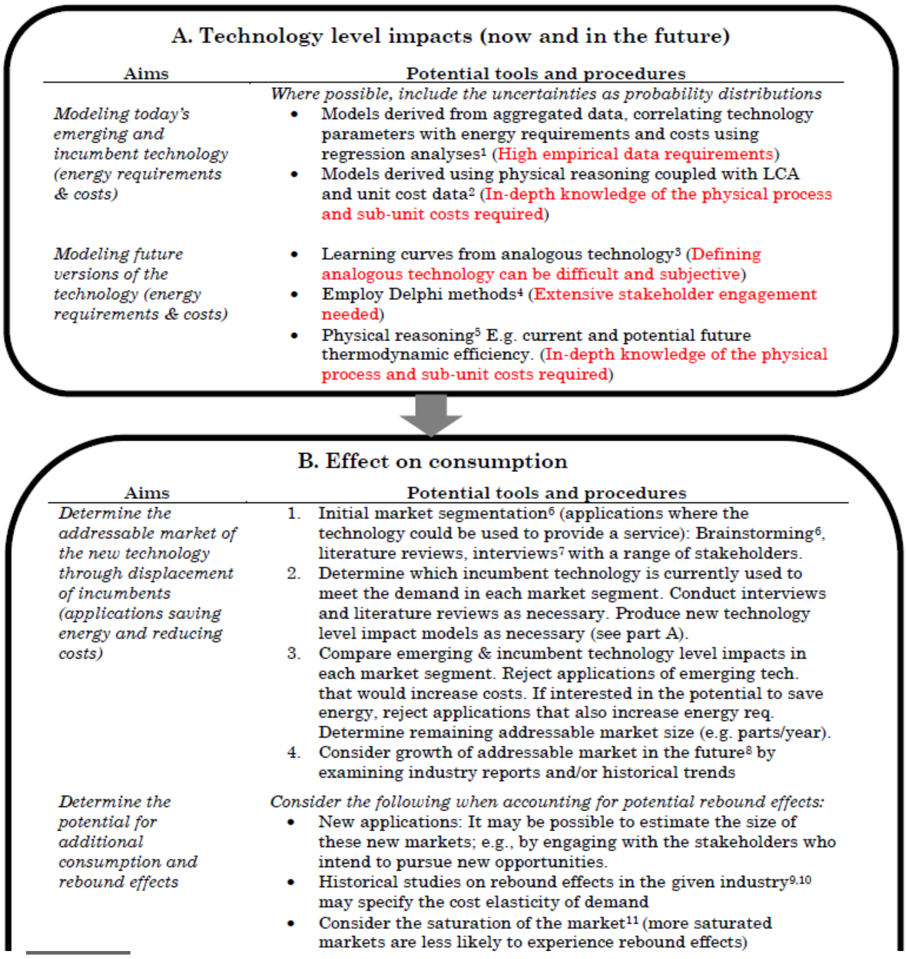


Figure 2: Proposed methodology. Numbering: recommended procedure. Bullet points: alternative tools. Notes: 1. Montgomery (2009); 2. Cooper et al. (2016); 3. Nagy et al. (2013) ; 4. Linstone (1975); 5. Nadeau et al. (2010); 6. Aulet (2013); 7. Rossie (2015); 8. Huang et al. (2015); 9. Gillingham et al. (2016); 10. Dahmus (2014); 11. Greening et al. (2000); 12. Van den Bulte (2002); 13. Morgan et al. (1998). References provide guidance on using the suggested tools

<heading level 2> Dealing with **uncertainty**

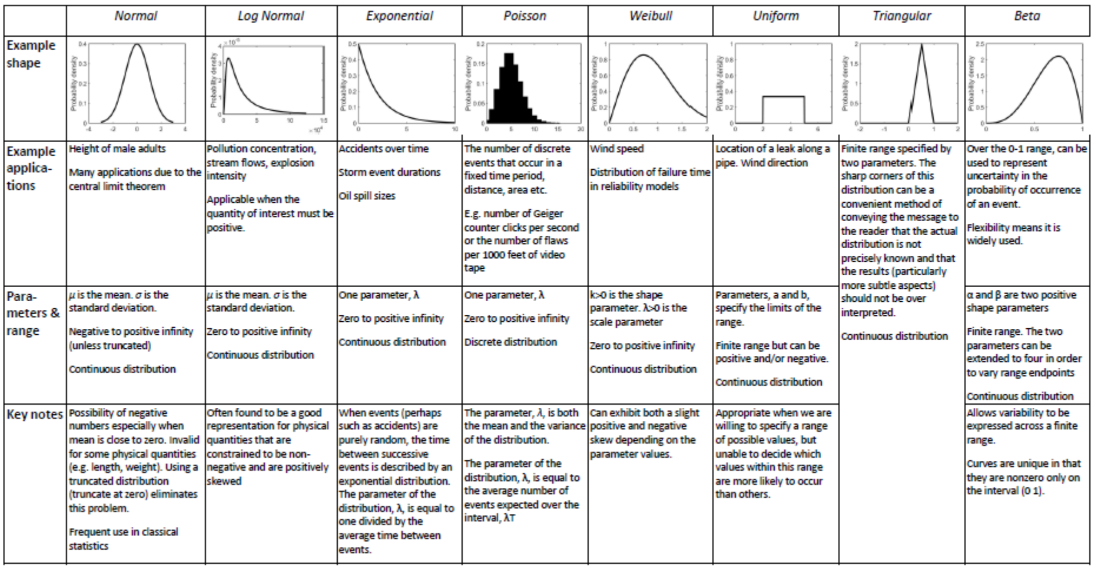
Uncertainties are high when performing a LCA, and these uncertainties are exacerbated when considering the applications of, and potential improvements to, the technology in the future. Here, we focus on the selection of probability distributions when modeling inputs from empirical data.

<heading level 3> Frequentist and Bayesian approaches

Many authors discuss the frequentist and Bayesian approaches to uncertainty, with Morgan et al. (1998) providing a good overview in the context of risk analysis in policy making. The frequentist approach defines the probability of an event as equal to the frequency with which it occurs in empirical data. The Bayesian approach accounts not only for the empirical data but for a prior belief regarding the probability (e.g., that a quantity can only take on positive values less than ten). The Bayesian approach takes advantage of all relevant knowledge known to a researcher but can introduce subjectivity. A researcher should specify the prior distribution/knowledge when implementing a Bayesian approach.

<heading level 3> Assigning distributions

The choice of probability distribution can have a significant impact on the calculated likelihood of event. Figure 3 presents some popular distributions, with example applications and key notes.



	Normal	*Log Normal*	*Exponential*	*Poisson*	*Weibull*	*Uniform*	*Triangular*	*Beta*
Example shape								
Example applica-tions	Height of male adults Many applications due to the central limit theorem	Pollution concentration, stream flows, explosion intensity Applicable when the quantity of interest must be positive.	Accidents over time Storm event durations Oil spill sizes	The number of discrete events that occur in a fixed time period, distance, area etc. E.g. number of Geiger counter clicks per second or the number of flaws per 1000 feet of video tape	Wind speed Distribution of failure time in reliability models	Location of a leak along a pipe. Wind direction	Finite range specified by two parameters. The sharp corners of this distribution can be a convenient method of conveying the message to the reader that the actual distribution is not precisely known and that the results (particularly more subtle aspects) should not be over interpreted.	Over the 0-1 range, can be used to represent uncertainty in the probability of occurrence of an event. Flexibility means it is widely used.
Para-meters & range	μ is the mean. σ is the standard deviation. Negative to positive infinity (unless truncated) Continuous distribution	μ is the mean. σ is the standard deviation. Zero to positive infinity Continuous distribution	One parameter, λ Zero to positive infinity Continuous distribution	One parameter, λ Zero to positive infinity Discrete distribution	k>0 is the shape parameter. λ>0 is the scale parameter Zero to positive infinity Continuous distribution	Parameters, a and b, specify the limits of the range. Finite range but can be positive and/or negative. Continuous distribution	Continuous distribution	α and β are two positive shape parameters Finite range. The two parameters can be extended to four in order to vary range endpoints Continuous distribution
Key notes	Possibility of negative numbers especially when mean is close to zero. Invalid for some physical quantities (e.g. length, weight). Using a truncated distribution (truncate at zero) eliminates this problem. Frequent use in classical statistics	Often found to be a good representation for physical quantities that are constrained to be non-negative and are positively skewed	When events (perhaps such as accidents) are purely random, the time between successive events is described by an exponential distribution. The parameter of the distribution, λ, is equal to one divided by the average time between events.	The parameter, λ, is both the mean and the variance of the distribution. The parameter of the distribution, λ, is equal to the average number of events expected over the interval, λT	Can exhibit both a slight positive and negative skew depending on the parameter values.	Appropriate when we are willing to specify a range of possible values, but unable to decide which values within this range are more likely to occur than others.		Allows variability to be expressed across a finite range. Curves are unique in that they are nonzero only on the interval (0 1).

Figure 3: Popular probability distributions. Informed predominantly by Morgan et al. (1998) and Montgomery (2009)

The central limit theorem establishes that, when independent random variables are added, their sum tends towards a normal distribution even if the original variables themselves are not normally distributed. This is why the normal distribution is commonly used. For example, in the case study presented later, a normal distribution is used to model the number of concept cars developed in the US each year (equaling the sum of distributions from individual car companies). Alternatively, technology inputs (e.g., die masses and electricity requirements) are assigned uniform distributions because a range of values is known but there is no evidence to suggest that a particular value is more likely to occur than any other (see Table S3 of the supporting information on the Web).

If sufficient empirical data has been collected it is possible to use statistical methods to select a distribution and estimate its parameters. Potential distribution shapes can first be evaluated by plotting the data as histograms. Subsequently, the kurtosis of the data, which is a measure of how outlier-prone a distribution is, may be calculated. Quantile-quantile plots of the data may also be used to visually inspect the correspondence of the data to a chosen distribution. Montgomery (2009) provides detailed instructions on kurtosis calculations.

<heading level 2> Technology level impacts (now and in the future)

The energy and cost impacts of a new technology will likely vary across the range of possible applications. For example, it may be cheaper and require less energy to use a plastic AM process to produce a one-off component (e.g., personalized insoles), but injection molding may be cheaper and less energy intensive for mass produced parts (e.g., plastic lunch-boxes). Lifecycle energy and cost models should be constructed for each relevant technology as functions of key technology characteristics (e.g., regarding AM, the chamber temperature for extruding different plastics) and market characteristics (e.g., the number of lunch-boxes and the type of plastic needed). The models can be used to compare the technologies in different market segments rather than relying on extrapolation from lone case studies. It may be necessary to model multiple conventional technologies if potential applications of the new technology span existing markets (e.g., autonomous vehicles might be used to undertake some journeys currently completed using passenger cars *and* trains).

<heading level 3> *Learning curves and future technology costs*

The cost of a new technology may decrease over time. Multiple laws have been proposed to predict technology improvement. For example, Moore's law predicts the exponential growth in the number of transistors on a dense integrated circuit (Moore 1965) and is widely interpreted as meaning that the cost of a technology decreases exponentially with time. Wright's law, originally regarding aeroplane production, predicts that production cost decreases as a function of cumulative production (Wright 1936). Nagy et al. (2013) review the ability of six such postulated laws to predict the cost of production across 62 technologies. They find that Moore's law and Wright's law are, in the absence of other knowledge, the best methods at predicting progress and that they are typically equivalent because an exponential decrease in cost is often accompanied by an exponential increase in production. Elsewhere, Nadeau et al. (2010) emphasize that the learning process is not guaranteed, with major cost elements not necessarily aligned with major opportunities for cost reduction. They advocate the use of process-based cost modeling, requiring a detailed knowledge of the cost structure but allowing intelligent predictions of future cost without having to rely on learning curve laws.

<heading level 2> Effect on consumption

The effect of the emerging technology on aggregate consumption will depend on the scale at which it is used, and the degree to which the final applications represent displacement of incumbent technology versus new, additional, consumption.

<heading level 3> Displacement of incumbent technology

The scale of use depends on both endogenous factors (properties of the emerging technology) and exogenous factors (properties of the marketplace and customer/manufacturer behavior).

Initial estimates of the addressable market will come from brainstorming, see Aulet's (2013) guide to brainstorming market segmentation for new technologies, and searching the literature for where others have speculated that the technology could be useful. Researchers can then conduct interviews with industry experts and get their perspectives. A range of stakeholders should be engaged otherwise opportunities might be missed and/or infeasible applications included. The estimate of the addressable market should likely be a distribution given the uncertainties.

The technology level models can be applied to the addressable market in order to determine the sweet spots: applications where the new technology is both environmentally beneficial and cost effective. Future growth of these sweet spot applications can then be calculated from industry reports (sometimes these include corresponding uncertainty) or historical trends. A technology diffusion analysis can then consider how quickly the emerging technology displaces incumbents in these applications, determining a "scale of use" for any future year.

Figure 4 shows the results of implementing the methodology in order to find the environmentally beneficial scale of use for an emerging technology in 2030 (see the later case study). As the histogram plots progress from left to right, the size of the addressable market shrinks as it is considered through multiple filters. First, the technical market size: can the technology provide the service, or for a manufacturing technology, feasibly make the part? Second, the energy demand associated with the new technology is compared to conventional technologies using the energy models derived as part of *Technology level impacts (now and in the future)*: can the new technology save energy across the technical market? Third, cost comparisons are made with conventional technologies using the cost models derived as part of *Technology level impacts*: can the new technology save money across the energy-saving market? Fourth, a range of technology diffusion scenarios (see *Technology Diffusion*) allow the size of the market to be predicted by any given date.

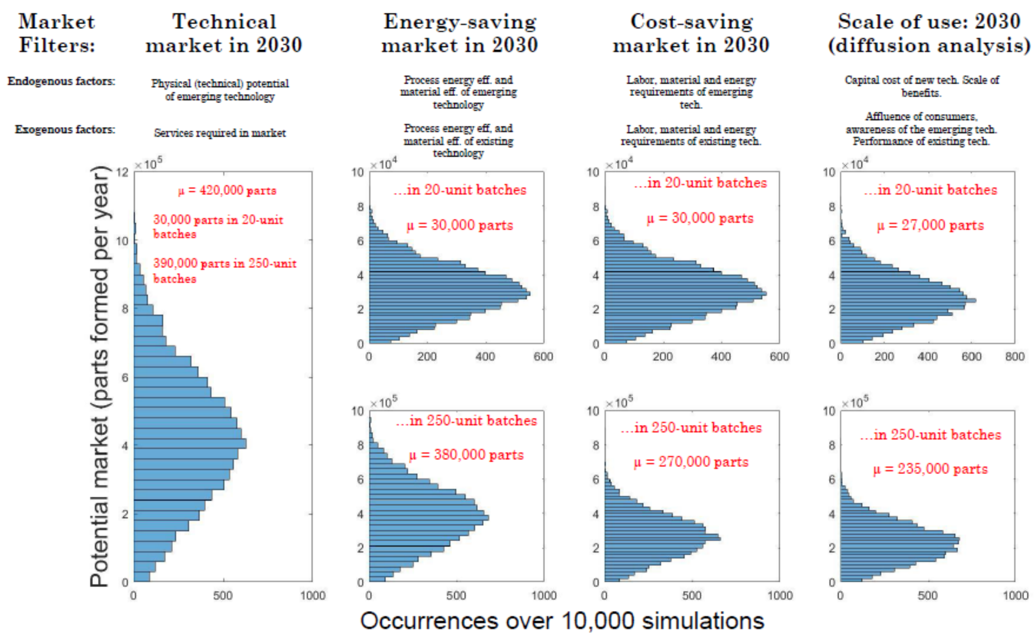


Figure 4: The effect of "filters" on the addressable market. Distribution from 10,000 Monte Carlo simulations

<heading level 3> Additional consumption

More work is required to understand the complex dynamics between new innovations, prices, and overall demand for materials and energy. However, summarizing the lessons learned from existing work, those engaged in prospective analysis should consider the following:

- *New applications.* A researcher is likely to have discovered (while performing a literature review and conducting stakeholder interviews) any intentions to use the emerging technology in new applications. For example, cheap 3d printing might be used to make personalized products for consumers and prototypes for manufacturers that otherwise would not have been made. These items are not replacing, and are only adding, to current consumption. It may be possible to estimate the size of these new markets; for example, by engaging with the stakeholders who intend to pursue these new opportunities. It may be necessary expand the system boundaries of the analysis in order to take into account any broader environmental benefits associated with the additional consumption.

- *Greater consumption in the same market.* It may be possible to predict the effect of lower prices on consumption by calculating the cost elasticity of demand using historical consumption and price data. For example, Tsao et al. (2010) found that mankind has historically spent around 0.7% of GDP on lighting. Elsewhere, the cost elasticities of demand are reviewed for various energy products across developed and developing countries (Gillingham et al. 2016) and for space heating and transport applications in the US (Thomas and Azevedo 2013). The rebound effect associated with new hybrid vehicles and train systems has been examined by Haan et al. (2007) and Spielmann et al. (2008) respectively, and Fouquet and Pearson (2012) also examine the lighting rebound. Dahmus (2014) considers historical rebound effects across multiple material production and transportation technologies. Historical precedents do not make rebound effects inevitable, but they should be considered.

- *Saturated markets may temper rebound effects.* A lower cost technology may not prompt additional consumption if the market is nearing saturation. For example, previous researchers have found that the aggregated energy rebound in developed countries is low (Greening et al. 2000) compared to developing countries with lower material wealth (Roy 2000; Antal and Van den Bergh 2014).

<heading level 3> Technology diffusion

A range of scenarios should be considered in order to anticipate how quickly the technology is picked up by customers. The diffusion scenarios may be informed by: (1) semi-structured interviews with industry experts, employing the Delphi method as described by Linstone (1975); (2) sales of the new technology if they exist; (3) historical analyses of analogous technologies. Analogs may be chosen because they belong in the same industry. Pae and Lehmann (2003) and Van den Bulte (2002) present many aggregated diffusion curves for different industries. Alternatively, Thomas (1985) argues that analogs can be chosen by defining broader similarities; for example, the degree of social interaction (word-of-mouth, social media etc.) between potential users, the costs of the technology and the relative affluence of potential users, and network effects such as the degree to which a surrounding infrastructure is needed in order to support the innovation (e.g., lengthy and costly certification procedures are required for new aerospace parts) (Peres et al. 2010). Considering a range of adoption scenarios is necessary because, as highlighted by Massiani and Gohs (2015), a pitfall in anticipatory diffusion modeling is the large range of historical precedents a researcher could use to select parameter values. It is recommended that researchers either assign a probability distribution to the diffusion curve (see the later case study) or explore high, medium and low adoption scenarios, as demonstrated by Huang et al. (2015).

<heading level 2> Prospective impacts and feedback to technology developers

Prospective impacts for a year of interest can be calculated by applying the technology level impact models to the results of the diffusion analysis (see the "scale of use" distribution in Figure 4). The impact will be the net effect of a switch from old to new technologies in those applications that represent displacement of incumbent technology. The impact will be the gross effect only of applying the emerging technology to those new applications that represent additional consumption and rebound effects.

In order to account for the compounded uncertainty it is recommended that a Monte Carlo analysis is used in which a value is drawn at random from the distribution for each input (Morgan et al. 1998). This set of random values defines a set, or Monte Carlo simulation, and the corresponding output value is calculated. Repetitions of this procedure produces an output distribution, illustrative of the uncertainty in the final results. In order to provide valuable feedback to technology developers it is recommended that key technology and market uncertainties (e.g., production rate of a manufacturing technology) be altered and the simulations repeated in a sensitivity analysis. Response surfaces may be generated if multiple parameter variations are of interest.

<heading level 1> Potential impacts of a new manufacturing process

The proposed methodology is used here in order to estimate the potential energy and cost savings in the US car industry by 2030 from the development of a new ISF process for making prototype sheet metal parts. Car companies produce large sheet metal parts (e.g., hoods, doors and fenders) in-house.

Car production is synonymous with mass production; however, during prototyping small batches of identical parts are produced. In mass production, forming tools are made from steel and iron; for lower volume part production, low melting resins and metals, such as zinc, are cast and machined to the final shape (ASM 1995; Bernard et al. 2001). These tools take several weeks to manufacture, whereas ISF production can begin as soon as the part design and forming tool path has been finalized. ISF is, however, a slow process (0.1-1 parts per hour, including preparation and removal time) compared to drawing.

During early part design, up to 20 units may be produced using zinc (or resin) dies. Engineers use these parts to examine the aesthetic appearance of the components, try various fastening methods, and experiment with stone peck (impact) tests on parts and fatigue tests on small assemblies. During full vehicle prototyping, around 250 more units are made of each part using new, updated zinc die-sets. For each part design, therefore, 270 copies are produced during prototyping using two different sets of dies (20 copies on one die-set and 250 copies on the other). Figures S1-S3 in the supporting information on the Web show the total lead time to produce different numbers of parts using alternative sheet metal forming (SMF) technologies. It would take over a year to make even a moderate number of parts (2,000 units) using ISF, compared to less than 3 months using conventional drawing. ISF is unable to compete at production volumes in the car industry; however, it should be noted that in lower volume industries such as aerospace and HVAC this is not necessarily the case. In light of these lead time considerations, this analysis focuses on the use of ISF to make 20-unit and 250-unit batches of parts. The baseline analysis considers using ISF to displace low-volume zinc die-set part production. Interviews with car companies and die makers, however, revealed that car companies sometimes use single sided zinc or resin dies in fluid cell forming (FCF) presses in order to reduce tooling costs. Looking to the future, it is important to understand the potential energy and cost savings of using ISF compared to these alternative forming methods, as well as compared to traditional zinc die drawing; see *Guiding technology development* later in this paper.

<heading level 2> Technology level impacts – energy and cost models

Physically reasoned models for ISF, drawing, and FCF are presented in Cooper et al. (2017) and Cooper and Gutowski (2016) respectively. The boundaries of the analyses are shown in Figure 5. The energy requirements and costs of *using* the formed parts are assumed irrelevant because the final part weight and geometry are likely to be similar irrespective of forming method. The models are presented in full in Section 3 of the supporting information on the Web and are used to predict per-part primary energy requirements and costs (mean and standard deviation) based on the final part material (typically steel or aluminum), size (surface area, thickness, and depth), and the lifetime number of parts produced on the die-set. The impacts and costs of a die-set are amortized (allocated equally) over the total number of parts produced using that die (20-unit or 250-unit batches). For ISF, it is also necessary to know the speed with which the tool traverses the sheet, and the incremental step size with which the tool progresses into the sheet after each tool path orbital. The following realistic default values (measured values already being used in research and development) have been used: 0.5 mm step size and 5 m/min tool speed.

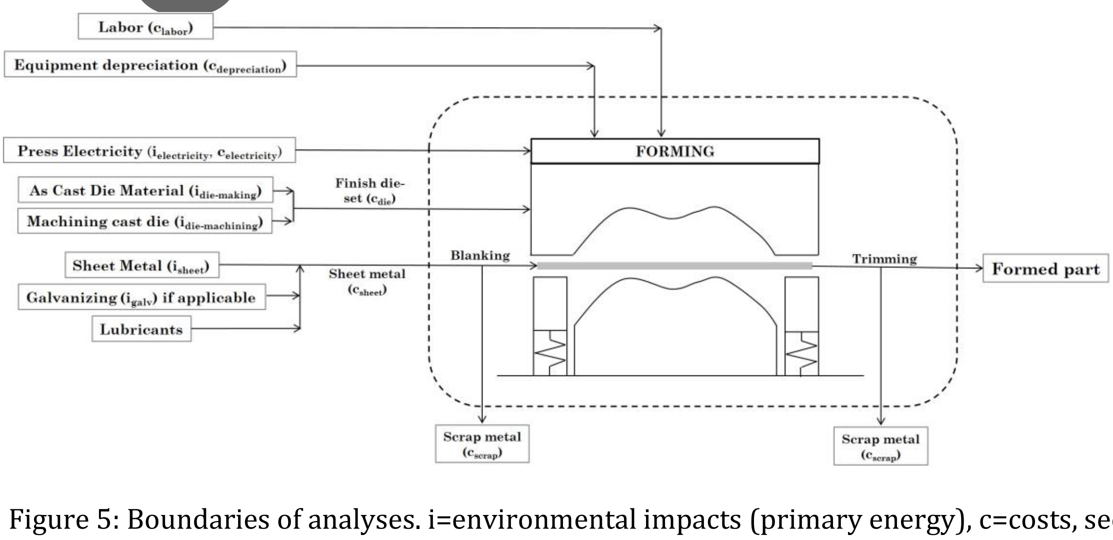


Figure 5: Boundaries of analyses. i=environmental impacts (primary energy), c=costs, see Table S2 of supporting information on the Web. The 'recycled content' method is used for all analyses.

<heading level 2> Consumption in 2030

By 2030, it is estimated that ISF could be used to form a mean of about 260,000 sheet metal parts per year. For these parts, ISF production will be cheaper and less energy intensive than conventional zinc die drawing. There are many uncertainties, including: (1) the number of part geometries (within a new vehicle) that can be formed using ISF; (2) the number of new cars that will be developed in the US in 2030; (3) the number of part geometries (in 20-unit or 250-unit batches) for which ISF production will reduce energy consumption and costs; and (4) the expansion of ISF across industry from a current position of low or trivial use. Distributions were defined for each of these uncertainties as described in the sub-sections below. Figure 4 summarizes the uncertainty in each consideration (technical, energy, cost, technology diffusion). Section 4 of the supporting information on the Web presents the raw data, and the mean, standard deviation, and kurtosis of each distribution.

<heading level 3> Technical market size by 2030

A typical inventory of sheet metal parts (and blank sizes) in an American passenger car is presented in Omar (2011). The material is assumed to be low carbon galvanized cold rolled steel because, despite the use of some aluminum, steel remains the predominant material used in car sheet metal parts. The parts from Omar were compared to the ISF specification (Table 1) in order to determine if ISF can form the geometry. Side body panels, for example, are too large to be formed in even the largest ISF machines. It is assumed that ISF can form parts where blank dimensions are smaller than 1.5 m. It is unclear whether or not ISF can form larger parts where all blank dimensions are smaller than 2 m (the largest ISF frame size), as some excess material may be necessary as part of an addendum design. Referring to Table 2, the number of parts in a passenger car that may be made using ISF is therefore likely to range between 34 and 40, modeled as a normal distribution, $N(37,9)$, truncated below zero parts.

Historical data on new vehicle production (provided by a leading consultancy) shows that between 1995 and 2014 Ford introduced a mean of 5.4 car models per year (standard deviation: 2.6) and that Ford accounted for a fifth of US domestic production. These numbers correlate well with personal communications the authors had with the Ford team responsible for developing new products. Combined with current US car production growth rates (3.2% per annum), these numbers suggest that by 2030 a mean of 41 new cars will be developed each year across the US (standard deviation of 20), modeled as a normal distribution, $N(41,400)$, truncated below zero parts. The distribution of new parts that ISF could technically make by 2030 ($X_{\text{technical potential}}$) is therefore given by equation 2, resulting in a mean of approximately 420,000 parts as shown in the “Technical market in 2030” column of Figure 4.

$$X_{\text{Technical potential}}\,[parts/\,year] \sim 270 \times N(37{,}9) \times N(41{,}400)\ (2)$$

<heading level 3> Energy and cost saving market size

The energy requirements and costs of ISF and zinc die drawing were compared using the models described earlier in this case study. The results are shown in Table 2 as mean savings (standard deviation equivalent to 30% of the mean for energy savings and 20% of the mean for cost savings).

Car part	Production number: 20 parts		Production number: 250 parts	
	Cost savings (USD/part)	Energy savings ($MJ_{primary}$/part)	Cost savings (USD/part)	Energy savings ($MJ_{primary}$/part)
All dimensions equal to or less than 1500mm				
Front door outer - 2 per car	36634	56573	7691	-32295
Rear Door outer - 2 per car	36923	59141	11865	9277
Front Fender - 2 per car	38531	86800	14712	61133
Trunk outer - 1 per car	38651	99822	5094	34302
Rear Wheel Well - 2 per car	36787	58819	10170	5256
Front door inner - 8 per car	35553	28328	17556	12806
Rear door inner - 8 per car	35554	26021	19233	12416
A Pillar - 2 per car	34772	9763	18912	-29646
B Pillar - 2 per car	34973	17164	16423	-22453
C Pillar - 2 per car	35679	26531	19685	-167
Roof Cross Members - 2 per car	34915	14931	16249	-40883
Trunk - 1 per car	39364	104163	14008	88565
All blank dimensions fit within 2000 mm x 1500 mm				
Hood outer - 1 per car	42537	176474	-865	63382
Roof outer - 1 per car	41871	165024	833	90910
Firewall (Dash) - 1 per car	39058	106940	5721	47429
Hood inner - 1 per car	43559	186850	11920	193081
Rockers - 2 per car	35228	25119	12376	-46260

Savings across a single vehicle development:

ISF application scenario	Part prototyping (20-unit batches)		Car development: 250-unit batches)	
	Cost (USD/vehicle)	Energy (TJ/vehicle)	Cost (USD/vehicle)	Energy (TJ/vehicle)
ISF used wherever technically viable	1.46 million USD	1.98 $TJ_{primary}$	587,198 USD	527,365 MJ
ISF used to maximize cost savings	1.46 million USD	1.98 $TJ_{primary}$	0.59 million USD	463,983 MJ
ISF used to maximize energy savings	1.46 million USD	1.98 $TJ_{primary}$	404,523 USD	0.87 $TJ_{primary}$
ISF used only when energy and money can be saved	1.46 million USD	1.98 $TJ_{primary}$	0.41 million USD	0.81 $TJ_{primary}$

Table 2: Energy and cost savings across parts in a single vehicle development (part prototyping and car development) if ISF is used instead of zinc die drawing to form parts. All part depths are conservatively assumed to be 0.3 m

Production of 20-unit batches results in energy and cost savings across all the parts considered. However, for 250-unit batches, some parts save energy but not cost (or vice versa). In this analysis, it is assumed that companies will only use ISF if they can save money compared to conventional forming techniques. Subsequently, there are only 27 parts per vehicle for which 250-unit batch production using ISF would save energy and money. As shown in Figure 4, the mean potential 250-unit market drops from 390,000 parts (technical potential) to 270,000 parts per year (production of these parts is technically feasible, requires less energy **and** lowers costs compared to conventional forming, see "Cost-saving market" column in Figure 4).

<heading level 3> Diffusion of ISF technology: market in 2030

Bass model diffusion coefficients were modeled as normal distributions: $p \sim N(0.017,0.0066)$; $q \sim N(0.47,0.09)$ as derived for industrial innovations by Van den Bulte (2002). His meta-analysis is the most comprehensive found in the literature; he aggregates over 1,500 diffusion coefficient values and provides confidence intervals on the mean values. It was assumed that ISF was not used to make any successful parts in 2016: S(2016)=F(2016)=0. The final results are shown in the "scale of use: 2030" column of Figure 4: a mean of 262,000 parts.

<heading level 2> Aggregate savings, technology displacement and the potential for rebound effects

The aggregated annual energy and cost savings in 2030 are calculated by multiplying per part savings (themselves distributions) by the "Likely 2030 market" distribution. In the baseline analysis it is assumed that ISF displaces, one-to-one, zinc die-set drawing, and does not cause a rebound effect. The subsequent energy and cost savings are presented in Figure 6. Section 5 in the supporting information on the Web presents details of this calculation.

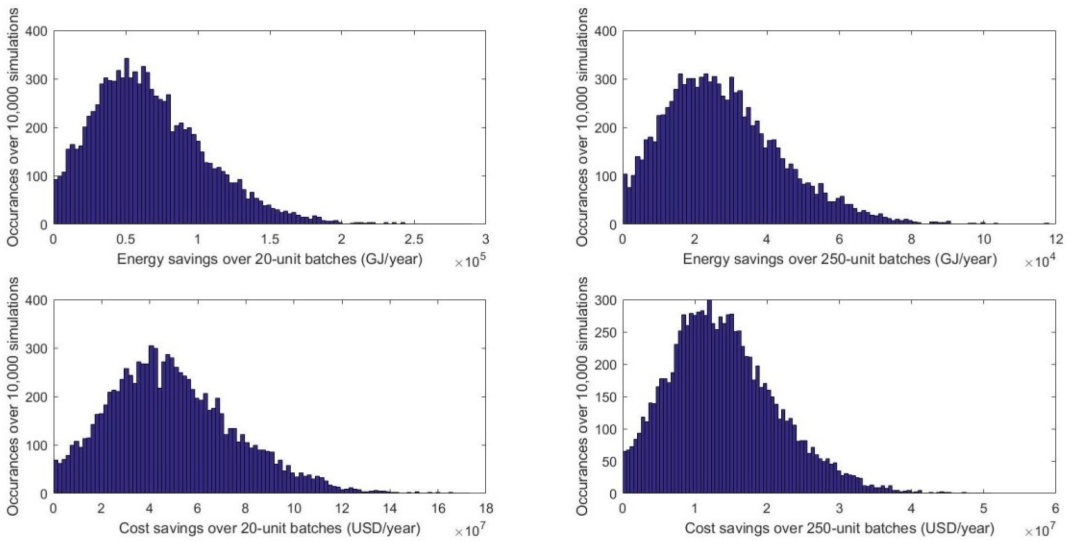


Figure 6: Total savings (from 10,000 simulations) across part prototyping (left column) and car development (right column) assuming ISF displaces zinc die drawing one-to-one

To evaluate if the baseline analysis reflects a realistic scenario, a series of interviews were conducted with industry experts: zinc die manufacturers, prototype part makers, design engineers, and managers at prototyping facilities. A list of the interviewees and questions that guided the discussions are provided in Section 6 of the supporting information on the Web.

A consensus emerged from the interviews that ISF could supersede matched die drawing for part prototyping because the potential cost savings are large. However, it was deemed unlikely that ISF will completely supersede zinc die drawing for car development in the foreseeable future. This is partly because car companies use the experience of drawing the 250-unit batches to inform the final design of both the part and the steel/iron drawing dies that will be used in mass production. ISF would be a poor indicator of material behavior during mass production because the forming mechanics differ from those in drawing. Improved finite element simulations may reduce the need for this learning step in the future (Hung 2016). Even if ISF production of 250-unit batches is currently unrealistic, Figure 6 shows that the main energy and cost savings will be derived from displacement of drawing dies in part prototyping (20-unit batches).

Could the cost savings from using ISF prompt an increase in car sales (a rebound effect)? In a historical study on US motor vehicle travel, Dahmus (2014) found low rebound effects in this sector. Focusing on new car sales, US Department of Transport data shows that over the last 45 years, despite rising prosperity and population, US new car sales have fallen, with 2014 annual sales 8% lower than in 1970 (DOT 2016). Domestic new car sales were 21% lower. We therefore cautiously hypothesize that increased US cost competitiveness may help shift the origin of US car sales, but that the effect on overall sales will be minimal.

<heading level 2> Guiding technology development

In order to guide technology development, sensitivity analyses considered the mean potential savings from using ISF by 2030 under the following circumstances:

(1) An increased ISF step size from 0.5 mm to 2 mm (process parameter change), reducing the forming time.

(2) A decreased ISF forming tool speed from 5 m/min to 4 m/min (process parameter), increasing the forming time.

(3) An alternative baseline scenario where the future alternative to ISF is FCF with a single (half) zinc die.

(4) An alternative baseline scenario where the future alternative to ISF is FCF with a single (half) resin die (modeled as RenShape 5166) for part prototyping (20-unit batches). Resin dies cannot be used to form 250-unit batches because they wear too quickly.

The results of this sensitivity analysis are shown in Figure 7. As shown, changes to the forming speed via step size and tool speed have a marginal effect on part prototyping energy savings, suggesting that technical efforts should focus on achieving the necessary part quality for this beachhead market. Growing use of FCF could halve savings in part prototyping and eliminate them in car development; the growth of FCF should be closely monitored by those espousing the use of ISF. The cost savings equivalent to Figure 7 displays similar trends.

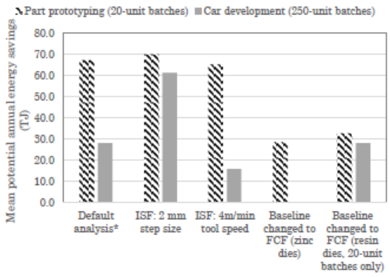


Figure 7: Savings from using ISF in 2030 (*ISF: 0.5 mm step size; 5 m/min tool speed. Baseline: drawing with zinc dies)

<heading level 1> Discussion

The approach described in this article explores the potential industry level impacts of an emerging technology. It extends the explorative analyses of anticipatory LCA by including the size of the technology's addressable market both now and in the future and considers technology diffusion, technology displacement and rebound effects. When testing different technology configurations (e.g., process speeds of a manufacturing technology), the energy and cost models change and the analysis recalculates the addressable market, revealing the industry level effect of design changes. Diffusion analyses are useful as they indicate when significant impacts might be expected to occur; for example, by acknowledging that not all a technology's benefits will be realized straight away, a government can choose a suite of CO_2 mitigation strategies in order to achieve a given roadmap towards lower emissions.

In a given application, it is possible that one technology is cheaper but requires more energy than another technology. This dynamic can then reverse in a different application; there is a danger that 'sustainable' technology, if used blindly, could result in an increase in overall energy requirements. Constructing energy and cost models as functions of different market segments, as demonstrated in this analysis, could help avoid this pitfall. For example, see Table 2 where it is demonstrated that ISF production of 250-unit batches of A pillars is cost effective but requires more energy than conventional production. This is because bespoke die-set manufacturing requires extensive manual labor and engineering time, and thus, the costs are high compared to the energy invested. Subsequently, ISF can still be cheaper than drawing even when ISF is more energy intensive.

Future application of a technology is dependent on some technical and commercial success. For example, the ability of developers to achieve the technical specifications defined in Table 1. The diffusion modeling employed in this work is informed by the diffusion of successful innovations in the past. There is therefore, as Rogers (2003) put it, an inherent pro-innovation bias with such modeling which policy makers should recognize. There is also a limit to the resources that can be spent modeling the potential market for a new technology. As described by Aulet (2013) it is important to realize that calculating potential new technology markets is an iterative process of "spiraling" toward the optimal answer. High uncertainties exist in prospective analyses; however, by considering the methodology presented in this paper, researchers will be able to produce more robust and transparent explorations of future impacts.

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