Increasing the Pace of Adoption and Commercialization: Capturing Expert Judgment at the Technical Frontier

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Climbing Out of the Valley of Death

“... the introduction and acceptance of new technology often depend more on social, cultural, and historical factors than on technological merit”

“...typical development times range between 2 and 20 years”

When to Adopt a New Technology?

• In-house expertise
• Consultants
• Outside vendors

How can these decisions and advice be evaluated?

Source: Wikimedia Foundation, NavAir, TeXample
What Do Experts Know?

• Experts are poor at certain types of judgments including
  • Additive
  • Systemic
• There is randomness in expert judgment, leading to inconsistency in small groups
• Decision rules are not always consistent
• Expert vary in degree of randomness and decision rules!
What Do Experts Know?

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Expertise or luck in business and engineering choices?
Can we capture and scale *expert knowledge* for new manufacturing technologies where:

1. Judgement is an *art*,
2. Experts are *few*, and
3. Potentially no one expert has all information?
Example Case: Metal Additive Manufacturing (MAM) for Aerospace

• Economic impact
  • Largest export value of U.S. manufactured goods (civilian engines and airframes) (US Census Bureau 2017)

• High barriers to new technology adoption
  • High risk industry with low tolerance for production uncertainty (Bonnin Roca et al 2017)

• State of maturity
  • MAM immature and tacit, aerospace inherently tacit (Bonnin Roca et al 2017; McNichols 2008)

• High level of expertise
  • Professionals with high level of expertise likely working with tacit cues (Abbott 1988)
Identifying MAM candidates: Many parts, few experts, arbitrary rules

- **4.5 million** Weapon System Parts
- **40k parts** where materials match AM; dimensions known, fit in build chamber
- **250 parts** with price >$1000
- **50 parts** with all necessary data; single-platform
- **40 non-critical**

Adapted from Tom Parks (LMI)
Presentation at DMC 2015
Implicit Knowledge: Which do you prefer?

Which part has the greater likelihood of being feasible for metal additive manufacturing within the next 5 years?

- Compressor Blisk (25cm diameter)
- Monocrystalline Turbine Blade (5cm x 15cm)

Source: GE Aviation, Wikimedia Foundation
Explicit Knowledge: What do you care about?

How does this part rate on the following attributes?

Monocrystalline Turbine Blade (5cm x 15cm)

Economics:
To what extent can a business case be made to produce this part using additive manufacturing?

- Not at all
- Slightly
- Moderately
- Very
- Extremely

Source: Wikimedia Foundation
Experts disagree (even with themselves!)

- **Consistent**
  - Similar
  - Distant

- **Close to Consistent**
  - (MFES < 4)
  - Similar
  - Distant

- **Inconsistent and Distant**
Aggregate experts are more consistent
Comparison to Filter Method (LMI)

Fuel Swirler

LMI: Excluded (price)

Our Method: High economic value (likely undervalued)
  Low criticality
  = 2nd part in average preference order
  and DCM

Source: Lawrence Berkeley National Lab

Adapted from Tom Parks (LMI)
Presentation at DMC 2015
Comparison to Filter Method (LMI)

Vanes

LMI: Excluded (size)

Our Method: High economic value (likely undervalued)
  Average criticality
  = 3rd part in average preference order, middle in DCM

Source: Ebay

Adapted from Tom Parks (LMI) Presentation at DMC 2015
Better Methods Move the Industry Forward

4.5 million Weapon System Parts

40k parts where materials match AM; dimensions known, fit in build chamber

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40 non-critical

Adapted from Tom Parks (LMI) Presentation at DMC 2015 (Current Best Practice)

Expert Knowledge
- Expert Y/N
- Industry-wide Expert Model
- In-house Expert Model
- Techno-Econ model
- Topology Optimiz. (sub-assemblies)

External Data
- Sketches, CAD, Databases, ...

ML

MAM Candidate Parts & Subassemblies

Engineering and Public Policy - Carnegie Mellon University
Better Methods for Individual Businesses

We can aid experts in technology commercialization questions like:

- Do we adopt the tech?
- Where in our business do we apply it?
- Who has the expertise? Where do we get it?

Our process measures and systematizes decision making practices within a business or consortium, providing 

*consistency, repeatability, and interpretability*
Thank you

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