

Cognitive Agents to Advance Sustainable Manufacturing

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What is Sustainable Manufacturing?

Sustainable *manufacturing* has been defined by the U.S. Department of Commerce as the creation of manufactured products using processes that minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers, and are economically sound (Haapala et al., 2013). Sustainable manufacturing is therefore a multidimensional optimization problem with components that must be evaluated within a temporal, geographical, and cultural context. Today sustainable manufacturing is challenged by incomplete data, knowledge, and supporting systems. This paper ponders the implementation of cognitive agents to help manufacturers identify and navigate sustainability trade-offs. It first discusses research advances needed to help manufacturers establish their sustainability targets. It then suggests that cognitive agents, inspired by early advances in carbon/energy management, can help a manufacturer maximize its profit while coordinating the achievement of the company's sustainability targets across its forward/reverse supply chains, manufacturing processes and systems, facility operations, product designs, and, potentially, future regulations.

Sustainable Manufacturing as Optimization

The above definition of sustainable manufacturing implies that the objective function is in the environmental dimension while the constraints are in the social and economic dimensions. A more realistic approach would modify this formulation so that the economic dimension is the objective and the environmental and social considerations are constraints as follows:

$$\begin{array}{ll} \text{MAX} & [\text{profit} = (\text{unit revenue} - \text{unit cost}) * \text{production volume}] \\ \text{SUBJECT TO} & [\text{environmental targets}] \\ & [\text{social targets}] \\ & [\text{other firm targets such as speed to market, quality, etc.}] \end{array} \quad (1)$$

Equation 1 is a corporation-wide manufacturing execution system problem based on setting environmental and social improvement targets as constraints. The introduction of environmental and social targets to the objective function would require the inherently arbitrary task of monetizing them. The inclusion of environmental and social targets in the constraint set is a more transparent expression of what is being valued by the corporation and makes clear what steps are being taken to improve sustainability beyond compliance with applicable legislation.

Setting Sustainability Targets

Advances in consequential life cycle assessment (cLCA) and social life cycle assessment (sLCA) are needed to help manufacturing firms set targets for social and environmental improvement. These targets can then be met with the assistance of coordinated cognitive agents using methodologies conceptually similar to analytical target cascading.

Consequential Life Cycle Assessment (cLCA). Life cycle assessment is a process through which the environmental impacts of a product or process are considered holistically, starting from material acquisition and ending with the product end-of-life, considering all the unit processes within the product system (ISO, 2006; Curran, 2006). Consequential LCA (cLCA) developed from the need to expand the system boundaries of LCA beyond just one product's life cycle to study the interactions of one life cycle with another (e.g., how does a large deployment of electric vehicles impact the electricity generation system?) (Finnveden et al., 2009; Hertwich, 2005; Ekvall and Weidema, 2004). Sustainable manufacturing exists at the nexus of multiple product and process life cycles, therefore necessitating advances in cLCA methods and data.

Social Life Cycle Assessment (sLCA). sLCA is an effort to fold social aspects of a product or system into environmental life cycle assessment. Jørgensen et al. (2008) reviewed methodologies for sLCA and summarized many of the mid-point indicators (e.g., in the areas of human rights, working conditions, labor practices, job creation, community communication, corruption, etc.) and end-point indicators (e.g., mortality, morbidity, autonomy, safety, security, opportunity, influence, etc.) that manufacturers and their stakeholders can consider during the process of establishing sustainability targets.

Environmental Impact Assessment Methods. Not all reductions in air/water emissions are equal. Research in the LCA community has identified this concern and is working on resolving LCA data spatially and temporally as well as interpreting the impacts of emissions from the perspectives of ecology and toxicology (Reap et al., 2008; Pennington et al., 2006). This progress is important to help manufacturing firms engage their stakeholders with relevant and unbiased data as sustainability targets are set and communicated.

Analytical Target Cascading. Analytical target cascading is an optimization methodology that decomposes a system into a hierarchy of subsystems and coordinates the optimization problems of the subsystems such that their solutions are consistent with the overall optimization solution for the top-level system (Kim, 2001; Nyström et al., 2003). Sustainability applications of target cascading can help firms navigate which specific products and manufacturing processes should be given which sustainability targets to assure the firm meets all of its goals without unintentionally compromising some goals (e.g., worker exposure to process chemicals) while in the pursuit of other goals (e.g., reductions in carbon footprint).

Cognitive Agents Advancing Sustainable Manufacturing

Cognitive agents are already emerging to help reduce energy consumption and carbon emissions from manufacturing enterprises. These cognitive agents range from control systems for lighting and HVAC based on occupancy to the control of machine warm-up and stand-by assignments based on production schedules. Cognitive agents are also working to optimize production schedules based upon time-of-day and peak demand electricity charges. As such automated

systems learn about their own energy consumption relative to alternatives available in the marketplace, it is imminently possible for such systems to generate suggestions for capital purchases of equipment such as motors and pumps to increase manufacturing process efficiency and eliminate waste. This takes the “Energy Treasure Hunt” concept and embeds it within cognitive control of the factory.

The next generation of cognitive agents applied to sustainable manufacturing will extend energy/carbon considerations to material and water consumption, air and water pollutant emissions, and *long-term* health impacts on workers. These metrics can be constantly evaluated relative to firm-level sustainability objectives leading to suggestions by cognitive agents for changes to facility operation or manufacturing process selection. Two hypothetical examples below illustrate how cognitive agents could begin to influence manufacturing process selection.

Energy Consumption of Alternative Manufacturing Pathways

A cognitive agent is endowed with models of energy consumption for alternative processes that could be used to make dies and molds, including both additive and subtractive manufacturing pathways. The cognitive agent considers the following problem:

$$\begin{array}{ll} \text{MIN} & [\text{Production Cost}] \\ \text{Subject to} & [\text{Reduce life cycle energy per unit product}] \end{array} \quad (2)$$

Morrow et al. (2007) built energy consumption models for tool and die production based on conventional and additive pathways and established criteria for which additive manufacturing would be selected in Equation 2 over conventional milling. It was found that products with high cavity percentage in the total volume were viable candidates for sustainable manufacturing via an additive pathway, in addition to cases where additive manufacturing created the possibility of new mold and die systems with lower *life cycle* energy consumption such as conformal cooling channels, heat sinks, protective coatings, and remanufacturing. Selected examples are provided in Figure 1.

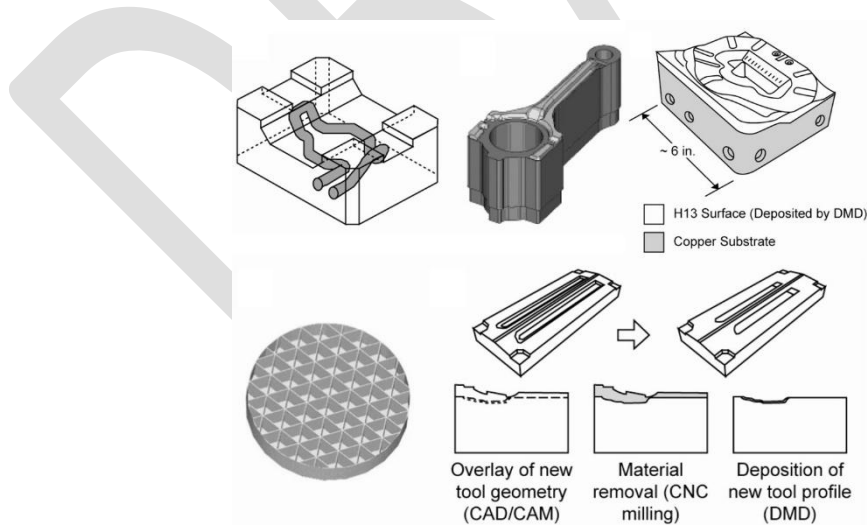


Figure 1. Applications of additive manufacturing that meet criteria of Equation 2. Clockwise: conformal cooling channels, wear protection coating on tool blank, multi-material heat sink, combined additive/subtractive remanufacturing of stamping tool to incorporate design changes, mirror backing for space application (Morrow et al., 2007).

Gas-Based vs. Water-Based Cutting and Grinding Fluids

Aqueous metalworking fluids are significant pollutants of water and cause long-term health risks for workers (Skerlos et al., 2008). Suppose a cognitive system is aware of alternative metalworking fluids such as gas-based minimum quantity lubrication systems and considers the following variant on Equation 1.

$$\begin{array}{ll} \text{MIN} & [\text{Production Cost}] \\ \text{Subject to} & [\text{Reduce Disability Adjusted Life Years (DALYs) for workers}] \\ & [\text{Reduce water consumption}] \\ & [\text{Reduce fats, oils, and grease emissions to water}] \\ & [\text{Quality, Throughput not reduced}] \end{array} \quad (3)$$

Based on materials being machined and process operating parameters, cognitive agents can advise as to whether environmentally conscious metalworking fluid alternatives exist. They also can adjust process parameters and process operations to enable the achievement of the imposed environmental and health constraints while minimizing cost. The cognitive agents are connected to complementary cognitive agents within the wastewater treatment system, the human resource system, tool/fluid/material procurement system, etc. such that *total* system costs to the firm are factored into the objective function.

Cognitive Agents beyond the Factory Walls

Future generations of cognitive systems would link decisions made within the firm to its forward and reverse supply chains. Already the efforts of large manufacturing firms to understand upstream carbon emissions have led to internet-based surveys intending to inform centralized databases regarding supplier carbon performance. Networks of cognitive agents could perform this task in an automated manner while offering, for instance, recommendations to procurement regarding supply chain design (Seuring and Müller, 2008) and recommendations to product design regarding how to enable “reverse” supply chains through targeted design for remanufacturing actions (Hatcher et al., 2001). This notion of collaborative cognitive agents working to simultaneously achieve sustainability objectives is fundamentally different than simply linking data systems containing environmental performance metrics. The linked cognitive agents would automatically generate opportunities for firms to collaborate toward reducing emissions via strategies that would yield greater profit for both firms than they could achieve if they acted alone.

This concept would not need to stop with communication between firm-level cognitive agents. Firm-level cognitive agents could connect with similar agents at the community and national levels to explore new opportunities for mutual gain. For instance where regulators are aiming to reduce the environmental impact of manufacturing firms, cognitive agents at the policy level could collaborate with cognitive agents at the firm-level to inspire novel solutions such as creating funding mechanisms for clean technology that could benefit manufacturers by overcoming financial hurdle rates and benefit society by achieving environmental improvements at less cost than traditional “command-and-control” regulation. Research has already begun to demonstrate how cLCA frameworks could begin to tackle such challenges by better understanding the interactions shown in Figure 2 that lead from regulation to production/consumption and ultimately to social and environmental impact (Whitefoot, 2011).

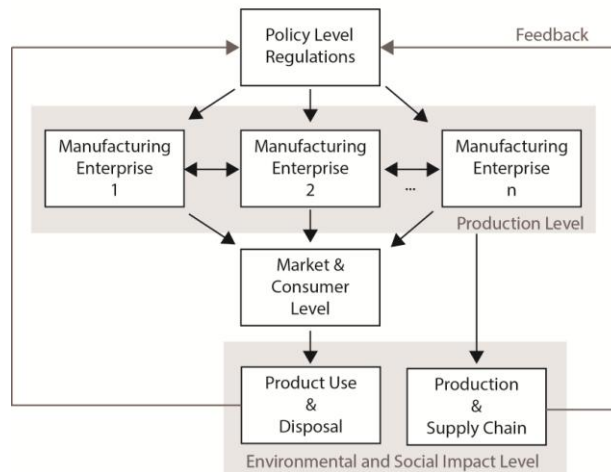


Figure 2. Interaction of systems influencing environmental and social impacts.

Summary

The complexity of sustainable manufacturing demands the creation of new knowledge and systems to set and achieve targets for least-cost social and environmental improvement. This effort can start with today's nascent cognitive systems for energy and carbon management and be extended to a broader set of environmental and health metrics. As cognitive systems gain access to LCA data emanating from the supply chain, they can influence the design of forward/reverse supply chains, factory siting decisions, and broader aspects of manufacturing process selection. Cooperation between cognitive agents influencing product design and manufacturing creates opportunities to improve product environmental performance and expand remanufacturing activity. The cooperation of firm-level and government-level cognitive systems can lead to new strategies for achieving sustainability objectives at lower societal cost than those borne by the legacy regulatory frameworks in place today.

References

- Curran, M.A. (2006). *Life Cycle Assessment: Principles and Practice*, EPA/600/R-06/060, U.S. Environmental Protection Agency, Cincinnati, OH.
- Ekvall, T.; Weidema, B. (2004). "System boundaries and input data in consequential lifecycle inventory analysis". *International Journal of LCA*, Volume 9, No. 3, pp. 161–171.
- Finnveden, G.; Hauschild, M.; Ekvall, T.; Guinee, J.; Heijungs, R.; Hellweg, S. Koehler, A.; Pennington, D., Suh. S. (2009). "Recent developments in lifecycle assessment". *Journal of Environmental Management*, Volume 91, pp. 1-21.
- Haapala, K.R., Zhao, F., Camelio, J., Sutherland, J.W., Skerlos, S.J., Dornfeld, D.A., Jawahir, I.S, Zhang, H.C., Clarens, A.F. (2013). "A Review of Engineering Research in Sustainable Manufacturing", *Journal of Manufacturing Science and Engineering, Transactions of the ASME*, in press.
- Hatcher, G.D., Ijomaha, W.L., Windmill, J.F.C. (2011). "Design for remanufacture: a literature review and future research needs", *Journal of Cleaner Production*, Volume 19, pp. 2004-2014.

- Hertwich, E.G. (2005). "Lifecycle approaches to sustainable consumption: a critical review". *Environmental Science and Technology*, Volume 39, No. 13, pp. 4673–4684.
- ISO (2006). *ISO 14040, Environmental Management–Life Cycle Assessment–Principles and Framework*.
- Jørgensen A, Le Bocq A., Nazarkina L., Hauschild M. (2008). "Methodologies for Social Life Cycle Assessment," *International Journal of LCA*, Volume 13, No. 2, pp. 96–103.
- Kim H.M. (2001). **Target Cascading in Optimal System Design**, PhD thesis, Department of Mechanical Engineering, University of Michigan, Ann Arbor, Michigan.
- Pennington, D.W., Margni, M., Payet, J., and Jolliet, O. (2006). "Risk and Regulatory Hazard-Based Toxicological Effect Indicators in Life-Cycle Assessment (LCA)". *Human and Ecological Risk Assessment*, Volume 12, No. 3, pp. 450-475.
- Morrow, W.M., Qi. H., Kim, I., Mazumder, J., Skerlos, S.J. (2007). "Environmental Aspects of Laser-Based and Conventional Tool and Die Manufacturing", *Journal of Cleaner Production*, Volume 15, Number 10, pp. 932-943.
- Nyström, M., Larsson, T., Karlsson, L., Kokkolaras, M., Papalambros, P.Y. (2003). "Linking Analytical Target Cascading to Engineering Information Systems for Simulation-Based Optimal Vehicle Design", *International Conference on Engineering Design*, Stockholm, Sweden, August 19-21, 2003.
- Reap, J., Roman, F., Duncan, S., Bras, B. (2008). "A survey of unresolved problems in life cycle assessment Part 2: impact assessment and interpretation" *International Journal of Life Cycle Assessment*. Volume 13, pp. 374-388.
- Seuring, S., Müller, M. (2008). "From a literature review to a conceptual framework for sustainable supply chain management", *Journal of Cleaner Production*, Volume 16, pp. 1699-1710.
- Skerlos, S.J., Hayes, K.F., Clarens, A.F., Zhao, F. (2008). "Current Advances in Sustainable Metalworking Fluids Research", *International Journal of Sustainable Manufacturing*, Volume 1, Number 1, pp. 180-202.
- Whitefoot, K. (2011). **Quantifying the Impact of Environmental Policy on Engineering Design Decisions**, PhD thesis, Design Science Program, University of Michigan, Ann Arbor, Michigan.

ⁱ Energy Treasure Hunts are an extension of the concept of lean manufacturing, aiming to eliminate energy waste. They were first developed by Toyota and now widely practiced by GE.