Sustainable Manufacturing with Cyber-physical Manufacturing Networks: Overview and Modeling Framework

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ABSTRACT

Cyber-physical systems (CPS) enable unprecedented communication between product designers and manufacturers. Effective use of these technologies both enables and requires a new paradigm of methods and models to identify the most profitable and environmentally friendly production plans for a manufacturing network. The Operating System for Cyberphysical Manufacturing and the paired Network Operations Administration and Monitoring software are introduced. These technologies guide our development of a mixed integer bilevel programming model that models the hierarchy between designers and manufacturers as a Stackelberg game while considering multiple objectives for each of them. Designers select and pay manufacturers, while manufacturers decide how to execute the order with the payment provided by the designer. To solve the model, a tailored solution method combining a decomposition-based approach with approximation of the lower level Pareto-optimal solution set is proposed. The model is applied to a case study based on a network of manufacturers in Wisconsin and Illinois. With the proposed model, designers and manufacturers alike can take full advantage of CPS to increase profits and decrease environmental impacts.

INTRODUCTION

Sustainability and environmental concerns continue to increase in importance to manufacturing stakeholders in the face of regulations, diminishing resources, and demand for more environmentally-friendly products [1, 2]. The United Nations predicts a population of 9.7 billion people by 2050, which will strain both material and energy resources [3]. Manufacturing will be particularly affected unless more sustainable manufacturing alternatives are found [1]. Redesign of manufacturing supply chains and products, as well as remanufacture and recover, are part of the new 6R concept of reduce, reuse, recover, redesign, remanufacture, and recycle [4]. Thus, in addition to redesigning products, designing sustainable production plans is a key goal of sustainable manufacturing [5]. New frameworks for identifying the most sustainable manufacturing strategies while remaining cost-competitive are needed [1].

To develop these frameworks, product designers and manufacturers must use cutting-edge technologies, such as cyberphysical systems (CPS) [6]. CPS connect physical components to cyberspace, allowing for distributed control of physical systems and machines, connected and responsive networks, and coordinated physical and engineered systems [7, 8]. Cyber-physical Production Systems (CPPS) integrate CPS with manufacturing science and technology to develop efficient, responsive manufacturing networks and factories [9, 10]. Recent development of an Operating System for Cyberphysical Manufacturing (OSCM) and the paired Network Operations Administration and Monitoring (NOAM) software (described later in this work), among other CPS developments like them, allow unprecedented communication between manufacturers and designers. However, the potential for CPS technologies to help designers and manufacturers identify sustainable production plans remains untapped.

Recent advances in sustainable product and supply chain design, processing, and machining make manufacturing more sustainable [11-13]. However, recent literature reviews in this space found that studies focus on empirical, qualitative findings, leaving quantitative decision-making tools for sustainable manufacturing underdeveloped [14]. Mathematical programming models quantitatively identify the most efficient or sustainable product design, production methods, or supply chains [15]. However, studies on manufacturing networks usually do not explicitly consider both sustainability objectives and the different goals and hierarchy of the stakeholders of a manufacturing network. Responsiveness and cooperation among stakeholders in a manufacturing network are imperative to achieving sustainable manufacturing [2]. Therefore, appropriately modeling stakeholder goals in a manufacturing network is essential. Emergent CPS enable responsive communication between designers and manufacturers, but quantitative tools that leverage this ability must be developed.

General, quantitative decision-making tools that identify sustainable production plans while considering objectives and hierarchy of all stakeholders could advance sustainable manufacturing considerably. There are several challenges to overcome in developing such tools. First, there must be some enabling technology or framework that can accurately and efficiently connect all stakeholders of a manufacturing network. Next, the tools must be applicable to any general manufacturing network as opposed to specific cases, which is often the approach of quantitative studies on sustainable manufacturing [14]. Finally, these tools must efficiently identify optimal, sustainable production plans of the manufacturing network considering objectives of all stakeholders. This work hypothesizes that new advances in CPS technologies motivate and enable such tools to be developed, and a new quantitative modeling framework is proposed. The proposed approach leverages anticipated advances of CPS like the OSCM/NOAM toolkit with a multi-stakeholder, multi-objective model and solution algorithm to optimize a manufacturing supply chain over sustainability objectives. This framework can be applied to any manufacturing network, enabling efficient identification of the most sustainable production plans for a given product.

The paper is structured as follows. First, relevant literature is presented on sustainable manufacturing, CPS, and supply chain design. Next, the CPS technologies that motivated this work, OSCM and NOAM, are introduced. The problem statement is then defined, and the model is formulated. Finally, the modeling framework is applied to a case study on a manufacturing network in the US states of Illinois and Wisconsin.

Novelties of this work include:

- Presentation of the OSCM and NOAM framework and software

- A quantitative decision-making framework that identifies the most profitable production plans with the least greenhouse gas (GHG) emissions for general, decentralized manufacturing networks connected with CPS technologies
- A hierarchical bilevel optimization model and tailored solution method that considers multiple objectives of designers and manufacturers
- Application to a manufacturing network in the US states of Illinois and Wisconsin

LITERATURE REVIEW

There are three critical bodies of literature relevant to this work. Sustainable manufacturing research is reviewed first. Next, research on manufacturing supply chain design and optimization is reviewed. Finally, recent advances in CPS research and development including OSCM and NOAM are described. Altogether, this work synthesizes concepts and research needs from each of these areas to construct a novel sustainable manufacturing network model that accounts for multiple objectives of the network's multiple stakeholders.

Sustainable Manufacturing

Sustainable manufacturing research at the product, process, and supply chain levels continues to advance [16]. Researchers have made considerable progress developing frameworks and tools to assess a specific product, process, or system's sustainability performance [14, 17, 18]. Sustainable product design that considers both production and consumption of the product is imperative [19]. Anastas and Zimmerman's [20] 12 principles of green engineering have guided green engineering design, and

Cooper-Searle et al. [21] reiterate the importance of material efficiency in combating climate change. Assessment frameworks for machining processes that include metrics for energy consumption, costs, environmental impact, and personal health and safety are continuously developed and improved [22]. Such frameworks and other approaches, including life cycle analysis (LCA) [23], have been applied to analyze impacts of many specific products and processes. For example, Su et al. [24] calculated the CO_2 emissions of different computer chair designs using LCA after the chairs were designed based on cost. Such works advance sustainable design and manufacturing but do so on a case-by-case basis, as opposed to more versatile systematic approaches.

When processes are assessed for sustainability, each process, such as turning [25] or milling [11] [26], is typically assessed individually. Detailed studies on energy or material improvement exist for a variety of processes. For example, smarter operation of hydraulic presses can result in significant energy savings [27]. Sinha et al. pursued economically feasible development of direct air capture of CO_2 using different metal organic frameworks with temperature swing adsorption technology [28]. Improving the energy and material efficiencies of powder metallurgy, an important technology in the burgeoning additive manufacturing area, has received considerable attention [29]. Additive manufacturing alternatives to conventional processes could reduce energy consumption and GHG emissions as demonstrated for additive repair of tooling for injection molding [30]. Remanufacturing is another important component of sustainability in manufacturing [31], and the US government promotes the concept through the Reducing Embodied-energy and Decreasing Emissions (REMADE) Institute [32]. These tools, frameworks, and analyses allow for sophisticated assessment of existing product designs and supply chains but cannot identify the most sustainable production plan out of a host of manufacturing options in a manufacturing network.

Existing frameworks and tools for assessing the sustainability of products, processes, and systems do not accommodate predefined processes well enough [12]. To address this gap, Alsaffar et al. [12] developed a framework that considered energy consumption and GHG emissions from several different processes, like laser cutting, bending, and machining. However, machining processes and the supply chain had to be pre-defined before calculating their environmental impact. Since different manufacturing processes can require considerably different amounts of energy, it is important to be able to systematically decide which processes to utilize in a sustainable production plan [33]. There does not yet exist a quantitative decision-making framework that systematically considers the trade-offs of cost and environmental impact among the many different machining and manufacturing process options within a manufacturing network [17]. If such a framework existed, product designers and manufacturers could quickly and directly identify the most sustainable production plan without having to estimate and compare impacts of every possible production plan.

Sustainable manufacturing systems can only be achieved when the objectives of all stakeholders are considered [2]. In many cases, multiple stakeholders in a manufacturing network, such as designers, manufacturers, etc., have multiple objectives. Identifying the most sustainable production plan while considering objectives of all stakeholders in a manufacturing network is a formidable challenge [34]. Manufacturing supply chain optimization models considering one manufacturer and multiple suppliers exist [35], but sustainability criteria outside of economic concerns are often not considered. Other emerging technologies in the manufacturing and machining spaces, like CPS, can be leveraged to develop sustainable and responsive manufacturing and production planning, but quantitative methods to leverage these potential advantages need to be developed.

Optimization in Manufacturing and Supply Chain Design

Researchers often directly include sustainable design criteria and objectives into manufacturing decision-making models and methods at the process, product, and supply chain levels [15, 36, 37]. Supply chains are modeled mathematically, and objectives such as cost or expected net present value, are frequently optimized [38]. Researchers use different methods to integrate environmentally-conscious decision-making into supply chain design/manufacturing network optimization. Some optimization frameworks coordinate product design and manufacturing process configuration for product families with a goal of constraining their carbon footprint [39]. Multi-objective optimization is a popular approach to design manufacturing systems. Nujoom et al. [13] minimized a manufacturing system's total cost and overall greenhouse gas (GHG) emissions. Another study minimized the total cost and GHG emissions of a manufacturing network of a large Taiwanese company [40]. Detailed environmental indicators such as Eco-indicator 99 have also been considered in multi-objective supply chain design while also maximizing economic objectives like profit [41]. Life cycle optimization (LCO) integrates LCA with mathematical programming and is a key tool for designing environmentally-friendly processes and supply chains [42]. Some studies have applied LCO to production networks to determine profitable and environmentally-friendly production pathways. Cradle-to-gate and cradle-to-grave LCO approaches were applied to a large-scale bioconversion product and process network [43]. Algal bioproduction networks have also been considered [44]. To the best of our knowledge, LCO has yet to be applied to machining and manufacturing networks.

Stakeholders at each point along the supply chain have multiple sustainability goals. However, there is often a hierarchy of decision-making among the stakeholders [39]. For example, decisions made by product designers limit and guide manufacturers' decisions. A popular approach to model this hierarchical structure employs the Stackelberg game from game theory, [45] which relies on bilevel programming to model the leader-follower aspect of the Stackelberg game [35, 46-48]. This modeling approach has been applied to several studies on decentralized supply chain design. For example, an integrated forestry and biofuel supply chain was designed with the forestry company as the leader, and the pulp company as the follower [46]. Similar approaches model timber harvesters as the leader and manufacturers as followers [48]. Shale gas production networks have also been modeled with the approach [47]. In all cases, modeling supply chains with the Stackelberg game resulted in more realistic and complete results compared to modeling all supply chain entities as one player. However, no previous approaches considered multiple objectives for the followers. Furthermore, works optimizing manufacturing networks often neglect modeling both the multiple stakeholders in the network as well as environmental objectives simultaneously [49].

In general, bilevel programming problems are difficult to solve (NP-hard) [50]. While there are many proposed alternative methods to solve them, only a few options exist to handle multiple objectives in the lower level. If the problem is structured in a certain way, there are methods to analytically identify optimal solutions [51-53].

However, if binary or integer decisions exist in the lower level multi-objective problem, tailored solution methods are typically developed [54].

Cyber-physical Systems

CPS are integral components of smart manufacturing and Industry 4.0 [55, 56]. While CPS technologies may be applied to a wide range of industries, manufacturing could use CPS to develop more efficient and sustainable CPPS [8]. Several web-based or software-driven CPPS have been developed recently. A web-based Wise-ShopFloor framework was proposed [57] and further developed [58] to plan machining sequences and job scheduling based on machine availability. The platform also controls the manufacturing process remotely.

While expectations of CPS to revolutionize the manufacturing industry are high [59], gaps remain in developing user-facing, decision-making tools to take advantage of these new technologies. CPS technologies that allow the many different stakeholders in different geographic locations within a manufacturing network to collaboratively exchange and share data and information are needed [6]. Models and algorithms that consider manufacturing processes, stakeholders, and systems would be particularly useful [56]. Transdisciplnary models and tools must fully take advantage of CPS technologies in information-driven economies [10]. Some emerging commercial examples, like Xometry [60], Protolabs [61], and Custompart [62], aim to provide pricing, lead times, and feedback with processes ranging from CNC machining to injection molding and 3D printing. However, these examples do not consider the environmental impacts of manufacturing. Other CPS technologies for manufacturing are also being developed, and the next section details such technologies that motivate this work.

NEW CPS TECHNOLGIES: OSCM

An open source manufacturing network framework is needed to connect different machines and handle transactions between customers and manufacturing providers. This gap is addressed in a collaborative work between Northwestern University and University of Illinois Urbana-Champaign. An Operating System for Cyberphysical Manufacturing (OSCM) was developed to enable manufacturing facilities connect their machines and capabilities over the internet to create a cyberphysical network of manufacturing machines that are visible and accessible to potential customers [63]. Additionally, OSCM provides the framework for connecting software assets or 'apps' to machines. In this framework, software assets are configured to match the capabilities and standard operating protocols (SOPs) for a particular machine. Using the OSCM web-services platform and software assets, potential customers can initiate job transactions on a machine using multiple visualization and verification tools. Users can access different manufacturing resources, study their capabilities, and schedule and price jobs. They can then choose the most desirable facility for their manufacturing transaction, easily get connected to the facility, share required files and information for the submitted job, and visualize their transaction in real-time.

The developed framework consists of four layers (Figure 1). The first layer is the physical hardware and machine controller. The second layer is the virtualization layer in which information of the machine is extracted from the local controller and shared with the operating system. Adapters developed for different controllers including Aerotech [64], Delta Tau [65], National Instrument devices [66], as well as MTConnect [67] compatible devices accomplish this task. The next layer, the operating system, exists in the cloud and allows manufacturing providers to connect their machines to the network and use different services of the network. The front-end network component NOAM (Network Operations and Administration Module) searches the network and manages transactions between users and machines, registrations and authentications, and multiple auxiliary assets to facilitate monitoring and verification of the process for both the users and service providers.

This network between manufacturing machines and users provides accessibility and transparency beyond what is possible with conventional approaches. Users can access information of a wide network of manufacturers as well as their capabilities, schedules, costs, locations, materials used, etc. all in a real-time and digitized online database. Therefore, this system enables unprecedented opportunities to select optimal manufacturing facilities and production plans. However, determining optimal production plans becomes challenging when considering the wide range of information accessible to users. New decision-making tools are needed to help users quickly and efficiently leverage new CPS technologies like OSCM to identify optimal production plans within a manufacturing network.

In summary, CPS technologies like OSCM that enable instant exchange of information between users and manufacturers are expected to see widespread adoption in the near future [59]. However, there is a need for new decision-making tools that leverage these new structural advantages. To meet this need, a mathematical programming model is developed that leverages the increased efficiencies made possible by CPS technologies like OSCM.

PROBLEM STATEMENT

This work proposes a decision-making model, motivated by emerging CPS technologies, that solves the problem of identifying the most profitable and most environmentally-friendly production plans of a product while ensuring manufacturers achieve optimal costs and equipment uptimes. In this problem, the product designer wishes to identify specific production plans that maximize profits (revenues minus payments to manufacturers and transportation costs) as well as minimize manufacturing and transportation GHG emissions, characterized by the 100-year global warming potentials (GWP) of emitted GHGs. GHG emissions are chosen as an environmental objective over others like energy consumed, water consumed, etc. due to the international surge of interest in mitigating climate change. Since GHG emissions of energy consumed throughout the manufacturing network are calculated, the impact of the energy consumed is still indirectly considered. Other environmental impacts are important and must be considered in future works. All part components are to be shipped to a central location for assembly. Manufacturers wish to minimize their costs and maximize the uptime of their equipment. They propose production plans that optimize these objectives based on the payments received from the designer. Therefore, the problem requires a method to model the hierarchy between designer and manufacturers while accounting for their multiple objectives.

In this problem, product designers submit details of their part – size, material, shape, machining requirements, etc. – as well as proposed payment plans to manufacturers who have different capabilities, costs, and locations. Payment plans in this context refer to the amount paid to each manufacturer by the designer. Under different payment plans, different manufacturers receive different amounts of funds. Manufacturers respond to the designer's proposed payment plans with a production plan (Figure 2). If a manufacturer receives payment from the designer, then that manufacturer produces some part components at a level consistent with the amount of funding received. Thus, different payment plans result in different manufacturers producing different amounts and types of part components (i.e. different production plans).

Raw material costs and processing costs are considered. Part components are manufactured from raw materials through a sequence of machining/manufacturing steps which may or may not occur at the same manufacturer's facility. If parts require further upgrading or finishing with capabilities the current manufacturer does not possess, the part must be shipped to a manufacturer that has the required capabilities. Each manufacturer has different production rates and energy requirements (electricity, natural gas, and compressed air) for each of its processes. Parts are transported via diesel-burning tractor-trailer trucks, and the designer pays transportation costs. Transportation costs are considered on distance and weight bases.

The problem is defined with a gate-to-gate system boundary and requires finalized product designs, with corresponding material compositions and dimensions, as an input. Thus, GHG emissions from production of the raw materials are not considered, as product design (i.e. material selection) is outside the scope of this work. GHG emissions can be reduced by re-designing products with different materials [20], and future works may consider such impacts. The problem also does not include disposal or end-of-life impacts. When product design and end-use steps are added, a more thorough cradle-to-grave approach could be adopted. As this is a demonstrative work, a gate-to-gate approach serves as a foundation for future works. Unit processes are single manufacturing steps (e.g. milling, casting, turning, etc.) or transportation steps.

To solve this problem, the following parameters/data are required:

- Location of each manufacturer
- Capabilities of each manufacturer
- Typical costs for each process
- Natural gas required for each process
- Electricity consumed by each process
- Compressed air required for each process
- Typical processing rates for each process
- GHG emission rates of each process
- GHG emission factors for electricity
- GHG emission rates for diesel-burning trucks in kg CO_2-eq/kg-km
- Transportation costs per kg-km
- Manufacturing requirements of each part component
- Volume and surface area of each component of the final part
- Availabilities and prices of each raw material
- Prices of the finished part components

Noteworthy assumptions include:

- Delivery trucks travel non-stop at a constant speed, and there is no delay or detour in transportation from one location to another
- Manufacturers' profits are accounted for within the costs they charge

- All produced parts and part components can be sold. Components produced beyond the required quota are assumed to be sold as spare components or to other assemblers.
- Final part components are shipped to the same site for assembly
- All manufacturers receive orders at the same time
- Manufacturers may not build or purchase new machining equipment
- Parts and components not required by the designer may not be produced
- All part components from a manufacturer are shipped in one shipment to the assembly site
- Fly-to-buy ratios for the same machining process are the same for each manufacturer

Major decisions include:

- Level of participation of each manufacturer in each manufacturing step of the part components
- The value of the payment provided to each manufacturer by the designer
- The amount of each raw material each manufacturer purchases
- Total production costs and equipment uptimes of each manufacturer
- The amount of each material to transport from each manufacturer to another manufacturer or the assembly center
- Total GHG emissions from production and transportation of the part components
- Designer profits

In this problem, the designer wishes to identify particular payment plans that maximize profits as well as minimize manufacturing and transportation GHG emissions. The manufacturers wish to minimize their costs and maximize the uptime of their equipment. This work proposes to model the hierarchy between the designer and manufacturers as a Stackelberg game [45]. In the Stackelberg game, the leader has perfect knowledge of how the followers will respond to its actions. Thus, the leader acts in a way that will result in optimal (to the leader) follower responses and actions. Extending this metaphor to the current problem, the designer (leader) chooses payment plans to the manufacturers (followers) that result in corresponding production plans, determined by the manufacturers, that have maximum profit for the designer and minimum GHG emissions subject to the manufacturers' pursuits of minimizing their costs and maximizing their equipment uptime (Figure 2).

Following precedent set in the manufacturing supply chain literature, a bilevel programming (BP) model is developed to represent the Stackelberg game structure [46, 68, 69]. Decisions of the leader and followers are represented by continuous and binary variables. Typically, BP problems are difficult to solve, especially when there are multiple objectives at both levels [50, 51, 54]. In the next section, the BP model proposed is first formulated, and a tailored decomposition-based solution strategy is proposed to solve it. After model decomposition, the model becomes a large-scale mixed integer, linear programming (MILP) problem, which may be easily solved.

MODEL FORMULATION

The model proposed in this work is a mixed integer, bilevel programming problem with multiple objectives in both the upper and lower problems. These problems consist of objective functions to be maximized or minimized as well as constraints and equations that define the problem's feasible solution space. In this section, the model's objective functions and constraints are first formulated. Subsequently, a solution method is described. In the following formulation, parameters are given in lower case, and variables are given in upper case. Note that parameters are input data to the problem, and the value of variables are to be determined by solving the problem i.e. finding optimal solutions. Index f denotes manufacturers, m denotes materials/intermediates/final part components, f' denotes manufacturer $f \neq f'$, and p denotes manufacturing processes.

The designer wishes to maximize profits:

$$\max \sum_{m}\sum_{f}\sum_{f'} pp_m \cdot TR_{mff'} - tc \cdot d_{ff'} \cdot \rho_m \cdot TR_{mff'} + C_f \tag{1}$$

where tc is the transportation cost in \$/kg-km, $d_{ff'}$ is the distance between manufacturer f and $f' \neq f$ in km, $TR_{mff'}$ is the volume of material m transferred to destination f' from f in m^3, ρ_m is the density of material m in kg/m^3, C_f is the value of the payment given to manufacturer f by the designer, and pp_m is the selling price of the final part component m. The designer also wishes to minimize manufacturing and transportation GHG emissions:

$$\min \sum_{f}\sum_{p}\left(ng_{fp} \cdot nge + ca_{fp} \cdot cae + ref_f \cdot pe_{fp}\right) \cdot X_{fp} + \sum_{m}\sum_{f}\sum_{f' \neq f} te \cdot \rho_m \cdot d_{ff'} \cdot TR_{mff'} \tag{2}$$

where X_{fp} is the operating level of process p at manufacturer f in throughput material or material removed (for milling or turning processes), te is the rate of GHG emissions from transportation in kg CO_2-eq/km-kg, ng_{fp} is the is the natural gas requirement of process p at manufacturer f in kg CH_4, nge is the natural gas combustion emissions factor, ca_{fp} is the compressed air requirement of process p and manufacturer f, *cae* is the emissions factor associated with the energy required to produce the compressed air, ref_f is the regional electricity GHG emissions impact factor for manufacturer *f*, and pe_{fp} is the electricity consumption of process *p* at manufacturer *f*. The designer also sets a time in which the order must be filled:

$$\sum_{p}\sum_{f}\sum_{f'}\frac{X_{fp}}{mr_{fp}}+\frac{d_{ff'}\cdot B_{ff'}}{ts}\leq ot \tag{3}$$

where mr_{fp} is the manufacturing rate of process *p* at manufacturer *f*, *ts* is the transportation speed in km/hr, $B_{ff'}$ is a binary variable that determines if any material was transported from manufacturer *f* to destination *f'*, and *ot* is the order time requirement in hours. $B_{ff'}$ is determined with the following constraints:

$$\sum_{m} TR_{mff'} \leq bm \cdot B_{ff'}, \forall f, f' \tag{4}$$

$$B_{ff'} = \{0,1\}, \forall f, f' \tag{5}$$

where *bm* is large enough to ensure that $TR_{mff'}$ can take its optimal value when $B_{ff'}$ = 1 and is zero otherwise. The manufacturers' problem follows next. Cost estimates for the different manufacturing processes serve as the basis for optimizing the manufacturing flow. Overall manufacturing cost estimation, despite considerable progress in manufacturing and information technology, is still very complex and challenging due to multiple unpredictable factors like true labor costs, stock costs, utility costs, order sizes, equipment costs, etc. [70]. Moreover, even for a given part, the specific manufacturability and raw material costs are still hard to quantify, especially considering the intricate nature of various manufacturing processes that require extensive engineering experience [71]. Therefore, the model employs a simplified cost model, which is a component of the manufacturers objective to minimize their overall cost:

$$\min \sum_m \sum_f mac_m \cdot P_{mf} + \sum_p \sum_f \left(vc_{fp} + ac_{fp} \cdot av_p + lc_{fp} \cdot lv_p \right) \cdot X_{fp} + FP_{fp} \cdot fc_{fp} \tag{6}$$

where mac_m is the raw material cost for material m, P_{mf} is the amount of raw material m purchased by manufacturer f, vc_{fp} is the cost to run process p if process p is a volume-based process (e.g. milling) in \$/m^3, ac_{fp} is the cost to run process p if process p is a surface area-based process (e.g. surface treatments) in \$/m^2, av_p is the area-to-volume ratio of the component to be processed in process p in m^2/m^3, lc_{fp} is the cost to run process p if process p is a linear process (e.g. welding) in \$/m, and lv_{fp} is the line-to-volume requirement of the component to be processed in process p in m/m^3. FP_{fp} is a binary variable that determines if process p at manufacturer f is used or not, and fc_{fp} represents all fixed costs of process p at manufacturer f (start-up costs, labor, capital costs, etc.). FP_{fp} is determined by the following constraints:

$$X_{fp} \geq \frac{FP_{fp}}{fpp}, \forall f, p \tag{7}$$

$$FP_{fp} = \{0,1\}, \forall f, p \tag{8}$$

where fpp is a scaling constant that ensures a minimum processing level if process p is selected at manufacturer f. The manufacturers also wish to maximize the uptime of their equipment:

$$\max \sum_f \sum_p \frac{X_{fp}}{mr_{fp}} \tag{9}$$

Manufacturing processes in this work are modeled as input-output processes. The following constraint governs how raw materials (e.g. steel, plastic, etc.) or intermediate materials (e.g. die cast steel, injection-molded plastic, etc.) are transformed into other intermediate materials or final part components:

$$P_{mf} + \sum_{f'} TR_{mf'f} + \sum_{p} mp_{pm} \cdot X_{fp} = S_{mf} + \sum_{f'} TR_{mff'} - \sum_{p} md_{pm} \cdot X_{fp}, \forall m, f \quad (10)$$

where mp_{pm} is a positive parameter that denotes if material m is produced through process p, S_{mf} is the amount of final component m stored/assembled by manufacturer/assembler f, and md_{pm} is a negative parameter that denotes if material m is transformed to a different intermediate or final material by process p. For example, in the case of an aluminum die casting process, md_{pm} = -1 for m = aluminum and mp_{pm} = 1 for m = die cast aluminum for p = aluminum die casting.

Only raw materials can be purchased:

$$\sum_{f} P_{mf} \leq ava_{m}, \forall m \in RM \quad (11)$$

$$\sum_{f} P_{mf} = 0, \forall m \notin RM \quad (12)$$

where ava_m is the availability of raw material m in m^3. Demand set by the designer must be met or exceeded if both the designer and manufacturers agree to do so:

$$\sum_{f} \sum_{f' \in FD} TR_{mff'} \geq dem_{m}, \forall m \in PM \quad (13)$$

where dem_m is the demand for final part component m required to assemble the part.

Costs for each manufacturer are calculated:

$$C_{f} = \sum_{m} mac_{m} \cdot P_{mf} + \sum_{p} \left(vc_{fp} + ac_{fp} \cdot av_{p} + lc_{fp} \cdot lv_{p} \right) \cdot X_{fp} + FP_{fp} \cdot fc_{fp}, \forall f \quad (14)$$

Thus, the overall BP problem is constructed:

min Designer profit (1)

min Overall GHG emissions (2)

s.t. Time requirements and logistics constraints (3)-(5)

min Manufacturers' costs (6)

max Uptime of manufacturers' processes (9)

s.t. Fixed costs and process selection constraints (7)-(8)

Material forming and machining operations (10)

Material availability (11)-(12)

Demand constraint (13)

Individual manufacturers' costs (14)

An important property of the model formulation above is its generality. If a designer has a product design as well as information on manufacturer capabilities, prices, and locations – perhaps from CPS-enabled technology – then this modeling framework can be applied to identify profitable production plans with low GHG emissions for that product.

Note that the optimal solutions of the lower level problem act as constraints for the upper level problem. Next, the problem is decomposed and reformulated into a single-level MILP. The lower level problem is replaced with its Pareto-optimal solutions for all values of the variables sent from the upper level to the lower level. The method is detailed in the following subsection.

Solution Method

A decomposition-based approach similar to the one proposed by Chu et al. [54] is now proposed and expanded to account for multiple objectives in the upper and lower levels by discretizing the Pareto-optimal space of the lower level problem.

The only variable set by the upper level required to solve the lower level problem is the payment provided to each manufacturer C_f. The manufacturers in turn send their responses to the leader with corresponding values of X_{fp} and $TR_{mff'}$ (the production plan). Thus, if C_f is bounded for all f, then the feasible range of each C_f may be divided into discrete steps. The lower level problem may then be solved to find a pair of values for X_{fp} and $TR_{mff'}$ for each Pareto-optimal solution for each step of each C_f. The Pareto-optimal solutions of each step populate the lower level Pareto-optimal solution set, used to solve the upper level problem.

Since the model is formulated in such a way that each C_f must have upper and lower bounds, the following optimization problems find the minimum and maximum feasible values for each C_f:

(C_Min)

$$cfn_f = \min \quad C_f, \forall f \tag{15}$$

s.t. Lower level constraints (7)-(8) and (10)-(14)

and

(C_Max)

$$cfx_f = \max \quad C_f, \forall f \tag{16}$$

s.t. Lower level constraints (7)-(8) and (10)-(14)

where cfn_f is the minimum possible payment assigned to manufacturer f, and cfx_f is the maximum possible payment assigned to manufacturer f. Now the range of possible payment values for each manufacturer can be discretized:

$$dc_f = \frac{cfx_f - cfn_f}{N_q - 1}, \forall f \tag{17}$$

$$cfq_{fq} = cfn_f + q \cdot dc_f, \forall f, q = 1 \ldots N_q \tag{18}$$

where dc_f is the step size for the range of payment values for manufacturer f governed by the number of discrete points desired N_q, and cfq_q is the payment made to manufacturer f at point q. Now that each C_f is discretized via (15)-(18), the following set of $f \cdot q$ multi-objective optimization problems emerges:

(Low_Cq)

$$\min \sum_m \sum_f mac_m \cdot P_{mf} + \sum_p \sum_f \left(vc_{fp} + ac_{fp} \cdot av_p + lc_{fp} \cdot lv_p \right) \cdot X_{fp} + FP_{fp} \cdot fc_{fp} \tag{19}$$

$$\max \sum_f \sum_p \frac{X_{fp}}{mr_{fp}} \tag{20}$$

s.t. Lower level constraints (7)-(8) and (10)-(14)

$$C_f = cfq_{fq}, \forall f \tag{21}$$

For each q problems for each manufacturer f, the payment value for manufacturer f is fixed by cfq_{fq}, while the payments received by other manufacturers can vary. The process is repeated $f \cdot q$ times to thoroughly search the feasible space defined by the minimum and maximum payment values to each manufacturer. The output of problem (Low_Cq) is a set of Pareto-optimal solutions demonstrating the trade-off between minimizing the manufacturers' costs and maximizing their equipment uptime. If each of the q Pareto-optimal curves for each manufacturer f are discretized with n points, the ε-constraint method is applied to (Low_Cq), resulting in $n \cdot q$ problems as follows [72]:

(Low_Cq_Single)

$$\underset{xq_{fpqn}, trq_{mff'qn}}{\arg\min} \sum_m \sum_f mac_m \cdot P_{mf} + \sum_p \sum_f \left(vc_{fp} + ac_{fp} \cdot av_p + lc_{fp} \cdot lv_p \right) \cdot X_{fp} + FP_{fp} \cdot fc_{fp} \tag{22}$$

s.t. $$\varepsilon_n \le \sum_f \sum_p td_{fpn} \tag{23}$$

Lower level constraints (7)-(8) and (10)-(14)

Fixed contract level for manufacturer f for problem q (21)

where td_{fpn} denotes the discretization of the equipment uptime objective into n possible values as per the ε-constraint method. (Low_Cq_Single) may be solved $f{\cdot}q{\cdot}n$ times, resulting in up to $f{\cdot}q{\cdot}n$ paired (cfq_{fqn},xq_{fpqn},$tr_{mff'qn}$) points that define the lower level Pareto-optimal solution set required to solve the upper level problem. When enough (cfq_{fqn},xq_{fpqn},$tr_{mff'qn}$) points have been found to adequately describe the lower level Pareto-optimal solution set, the original problem may be reformulated as a single-level, MILP problem:

(Multi_UP)

min Designer profit (1)

min Overall GHG emissions(2)

s.t. Time requirements and logistics constraints (3)-(5)

$$X_{fp} = \sum_q \sum_n xq_{fpqn} \cdot SL_{qn}, \forall f, p \quad (24)$$

$$C_f = \sum_q \sum_n cfqn_{fqn} \cdot SL_{qn}, \forall f \quad (25)$$

$$TR_{mff'} = \sum_q \sum_n trq_{mff'qn} \cdot SL_{qn}, \forall m, f, f' \quad (26)$$

$$\sum_q \sum_n SL_{qn} = 1 \quad (27)$$

$$SL_{qn} \in \{0,1\}, \forall q, n \quad (28)$$

where SL_{qn} is a binary variable that denotes if the lower level Pareto optimal solution at point q,n is chosen. Applying the ε-constraint method to (Multi_UP) results in the following single-level, single objective MILP problem:

(Final_UP)

min Designer profit (1)

$$\text{s.t.} \sum_{f}\sum_{p}\left(ng_{fp}\cdot nge+ca_{fp}\cdot cae+ref_{f}\cdot pe_{fp}\right)\cdot X_{fp}+\sum_{m}\sum_{f}\sum_{f'\neq f}te\cdot\rho_{m}\cdot d_{ff'}\cdot TR_{mff'}\leq\varepsilon_{u} \tag{29}$$

Time requirements and logistics constraints (3)-(5)

Lower level Pareto-optimal point selection constraints (24)-(28)

where ε_u is the value of the ε-constraint for the environmental objective in the upper-level problem.

The final challenge is determining the appropriate sizes of q and n. If q and n are too small, the solutions to Final_UP may not be satisfactory. If q and n are too large, the time required to compute all (cfq_{fqn},xq_{fpqn},$tr_{mff'qn}$) points becomes prohibitive. This problem is tackled by introducing an algorithm that increases q iteratively until there is no improvement in the solutions of (Final_UP) without constraint (29) (Figure 3). Then, the algorithm assumes that a number of (cfq_{fqn},xq_{fpqn},$tr_{mff'qn}$) points that is large enough to optimize the upper level cost objective (1) will also be large enough to optimize the upper level environmental objective (2). After a sufficiently large number of points is obtained, (Final_UP) is solved to generate the Pareto-optimal solutions for the designer. Note that only approximate solutions can be found with this method. If the number of (cfq_{fqn},xq_{fpqn},$tr_{mff'qn}$) is large enough, however, the approximation is assumed to provide satisfactory solutions.

CASE STUDY DEFINITION

The modeling framework and solution strategy are applied to a case study of a manufacturing network of 22 manufacturers in Wisconsin and Illinois. Five manufacturers are in Wisconsin, and the remaining 17 are in Illinois (Figure 4). At least

10,000 units of aluminum bearing brackets, rods, and steel gearbox housings must be fabricated. Finished part components are shipped to an assembly center in Fon du Lac, Wisconsin, a location between the two manufacturing groups considered in this work, for assembly (Figure 4). The geometries of the parts are depicted in Figure 5, and some operations that could be used to manufacture each part component are summarized in Table 1.

The data described in this section function as input parameters to the model formulated in the previous section for this case study. Wherever possible, data from peer-reviewed sources, government publications, or relevant databases are utilized [73-77]. Component selling prices (parameter pp_m in equation (1)) were estimated from similar parts found in an online search. The lower end of the prices identified in the search were used in this study as a conservative estimate of price. From this search, we estimated that the aluminum brackets can be sold for \$6.31, the aluminum rods may be sold for \$3.69, the steel front housings of the gearbox housing may be sold for \$22.31, the back housings for \$74.18, and the plastic rings for \$3.51. Due to the significant estimations and difficulty of estimating costs and prices, economic results from this model cannot replace rigorous economic estimation of production.

Locations and capabilities of manufacturers were extracted from multiple public online resources such as the Illinois Manufacturing directory, Manufacturing in Wisconsin's directory, and the manufacturers' websites [76, 77]. Estimated manufacturing capabilities and other information for these manufacturers are given in Table 2. To ensure the privacy of these companies, their names are not provided. While some of the manufacturing capabilities gathered are based on readily available descriptions of the manufacturer's industry sectors, core competencies, and provided services, there often was no clear information. For the sake of this work, manufacturing capabilities for companies with inadequate information are estimated based on products advertised on the manufacturers' websites. Approximate processing and machining rates (parameter mr_{fp}) for each process were estimated from Polgar et al. or industry data [78].

Longitude and latitude coordinates for each manufacturer were estimated. The coordinates were then used to estimate distances between all manufacturers as well as all manufacturers and the assembly location (parameter $d_{ff'}$). Distances calculated from online mapping/direction services might provide more accurate travel distances and times. However, such services are often incorrect due to road closures, traffic situations, etc., and there is no guarantee the delivery drivers will take the suggested path(s). Thus, distances were calculated via longitude and latitude as a rough estimate for the purposes of this work.

While the model presented in the preceding section can handle any number of input materials and processes, the presented case study considers 8 raw materials: aluminum, steel, cast iron, chromium steel, copper, brass, plastic, and magnesium alloy. 76 machining and processing methods, such as sand casting, milling, and powder coating processes, are considered. Not every material or process will be utilized in this case study, but the material and process options serve as a foundation for future studies and different product designs. Raw material costs (parameter mac_m) are retrieved from industrial market prices. Process costs, influenced by part complexity (how intricate required machining steps are), the manufacturing process (see description of equation (6)

), and material type, are estimated with online resources and industrial surveys [62, 79]. Process costs, energy use (see equation (2)), and processing rates for each process at each manufacturer were varied between 50% and 150% of the base process estimates to better model price and performance variability from manufacturer to manufacturer.

Data on each manufacturing process's electricity, natural gas, compressed air consumption and any direct emissions were retrieved from the EcoInvent database (version 3.4) [80]. If the process uses electricity, then electricity emission factors are used from the state in which the manufacturer is located to calculate indirect processing emissions [73, 74]. Diesel trucks are assumed to transport part components, so the GHG emission rate of diesel combustion and typical gas mileage of tractor-trailer trucks to model transportation emissions are used to calculate transportation emissions [75, 81]. GHG emissions are calculated from the amount and type of each energy source used, and IPCC impact factors are used to calculate GWP-100 [82] in equation (2). The designer's total production time (parameter ot in equation (3)) is set at 3,600 hours (or 150 days). Availabilities of each raw material (parameter ava_m in equation (11)) are set at 4 m^3.

RESULTS AND DISCUSSION

All computational experiments are performed on a DELL OPTIPLEX 790 desktop with Intel(R) Core(TM) i5-2400 CPU @ 3.10 GHz and 8 GB RAM. All the models and solution procedure are coded in GAMS 25.0.3 [83]. All MILPs were solved with the CPLEX 12.8.0.0 solver (IBM, Armonk, NY, USA). The q lower-level problems had over 4,000 equations, approximately 48,000 continuous variables, and approximately 1,750 discrete variables. The (Final_UP) problems had over 43,000 equations, 46,000 continuous variables, and approximately 3,600 discrete variables. The number of lower level Pareto-optimal solutions n found for each of the $f{\cdot}q$ problems was fixed at 10, q started at 9 and increased by 5 for each iteration of the solution algorithm. The algorithm tolerance τ in Figure 3 was set at 0.01, or 1%. The problem was solved in approximately 3,700 seconds of wall-clock time and 1,300 CPU seconds and required two iterations of the solution algorithm. Thus, the lower level Pareto optimal solution space was estimated with approximately 1,980 points.

Figure 6 displays the Pareto-optimal curve for the designer, highlighting the trade-off between GHG emissions and profit. Profits range from -$992,593 (losses) to $133,774, and corresponding GHG emissions range from 2,152 kg CO_2-eq to 3,000 kg CO_2-eq. Machining/processing emissions dominate overall GHG emissions. Even though each production plan features different manufacturers in different proportions, the overall ratio between transportation emissions and machining/processing emissions are similar for all solutions.

At the solution with the fewest GHG emissions, either exactly or slightly more than 10,000 units of each part component are made, satisfying the quota. More of the most cost-effective parts are made in the solutions with higher profits. Specifically, production of aluminum rods and plastic rings increases quickly. These components are relatively cheaper to make than the other components, so the designer can realize increased relative gains by overproducing these components, and the manufacturers enjoy increased process uptime. There is an area of the designer's Pareto-optimal curve where relatively small decreases in profits result in significant decreases in GHG emissions, and the reverse is also true. For example, the solution with the fewest GHG emissions emits 2,152 kg CO_2-eq with losses of $992,593. However, if the designer is willing to accept an increase in GHG emissions from 2,152 kg CO_2-eq to 2,225 kg CO_2-eq (increase of ~3%), then losses decrease dramatically from $992,593 to $281,696 (a drop of ~72%). These results clearly demonstrate the advantages of identifying trade-off solutions for production of different parts. Without the systematic, quantitative approach taken in this work, designers and manufacturers would have no means to identify these alternative production plans. Thus, they might not realize that minor changes to their production plan could result in a production plan they might prefer featuring significant improvement in profits or GHG emissions.

The results show it is possible to remain profitable while decreasing environmental impacts. Figure 6 highlights a compromise solution, chosen because the production plan is profitable, making $24,160 of profits with GHG emissions at 2,356 kg CO_2-eq, or 79% of the worst possible value of 3,000 kg CO_2-eq. The manufacturers have a Pareto-optimal curve depicting the trade-offs between their costs and cumulative production time. Manufacturers' possible costs at this compromise solution range from $2,091,635 to $3,538,656, and their cumulative production times range from 6,032 hours to 15,150 hours. Figure 7 and Table 3 detail the production plan for the compromise solution. The designer pays $1,906,728 to manufacturer 3, $223,564 to manufacturer 10, $26,050 to manufacturer 17, and $60,970 to manufacturer 22. Machining emissions of 2,007 kg CO_2-eq dwarf transportation emissions of 349 kg CO_2-eq. These results represent a further need for research and development of more energy-efficient machining technologies and processes.

Manufacturer 3 is a key manufacturer in the compromise solution. While charging a relatively high price compared to other manufacturers, manufacturer 3 is the closest manufacturer to the assembly center, minimizing transportation costs and emissions. Manufacturer 3 processes 4,023 kg of aluminum into 10,000 bracket bodies via die casting, milling, drilling, and painting. 19,240 kg of steel are processed into 7,755 gearbox back housings and 10,000 gearbox front housings via milling, drilling, welding, and painting. Manufacturer 10 mills, welds, and paints 4,025 kg of steel to make 2,245 gearbox back housings. Manufacturer 17 rolls 6,777 kg of aluminum into 28,784 rods, and manufacturer 22 molds 3,320 kg of plastic granules into 316,000 plastic rings. Total order time, based on transportation of the components and the longest processing time of all manufacturers, is 2,365 hours (~99 days). Manufacturers that could make the part components from raw material to completed component in-house were chosen whenever possible. Doing so decreases transportation costs, transportation emissions, and overall manufacturing and delivery time.

Figure 8 and Table 4 detail the production plan for the solution with the highest profit. The designer pays \$2,177,472 to manufacturer 10, \$398,237 to manufacturer 19, \$60,328 to manufacturer 18, \$31,945 to manufacturer 3, \$26,050 to manufacturer 17, and \$13,164 to manufacturer 22. Total time to produce and deliver the parts is 2,226 hours (~93 days). Total GHG emissions are 3,000 kg CO_2-eq, with 552 kg CO_2-eq from transportation emissions and 2,448 kg CO_2-eq from machining/processing emissions. The number of components produced by each manufacturer and their processing times are shown in Table 4. As in the compromise solution, manufacturer 3 is chosen to make aluminum bracket bodies as it is the closest manufacturer to the assembly center, limiting transportation costs. However, it is not the most cost-effective producer of the bracket bodies, so manufacturer 19 produces 9,304 of the 10,000 total bracket bodies, even though transportation costs are higher. Similarly, manufacturers 18 and 22 are both chosen to produce different numbers of plastic rings. Thus, the model identifies the trade-off between transportation costs and production costs and can find an optimal production plan taking this trade-off into account. Manufacturer 10 receives the largest payment because it is the only manufacturer that produces the steel components, producing 10,045 gearbox front housings and 15,014 gearbox back housings. Manufacturer 17 produces 28,784 aluminum rods. From these results, the aluminum rods, plastic rings, and gearbox back housings are more cost-effective to produce and transport than the bracket bodies and gearbox front housings. The designer could use these results to re-design the part so that production and transportation of all components are more cost-effective.

Figure 9 and Table 5 detail the production plan for the solution with the fewest GHG emissions. The designer pays \$1,678,828 to manufacturer 10, \$309,671 to manufacturer 3, \$90,836 to manufacturer 19, \$9,064 to manufacturer 11, and \$13,164 to manufacturer 14. Total time to produce and deliver the parts is 2,712 hours (~113 days). Thus, it takes longer to produce and transport the part in this solution than in the compromise solution and the solution with the highest profit. Total GHG emissions are 2,152 kg CO_2-eq, with 340 kg CO_2-eq from transportation emissions and 1,812 kg CO_2-eq from machining/processing emissions. The number of components produced by each manufacturer and their processing times are shown in Table 5. As in the compromise solution and the solution with the highest profit, manufacturer 3 is chosen to make aluminum bracket bodies as it is the closest manufacturer to the assembly center, limiting transportation emissions. However, it emits more GHG emissions producing each bracket body compared to manufacturer 19. Therefore, manufacturer 19 produces 2,209 of the

10,000 total bracket bodies, even though transportation emissions are higher. This result shows that, much like the trade-off between production and transportation costs, the model identifies the trade-off between transportation and production emissions. Manufacturer 10 again receives the largest payment, producing 10,000 gearbox front housings and 10,000 gearbox back housings. Manufacturer 11 produces 10,000 aluminum rods. Manufacturer 14 produces 10,476 plastic rings, just over the 10,000 ring quota. All components are produced exactly at or close to the 10,000 unit quotas. Doing so decreases transportation and production emissions, but results in an economic loss of $992,593.

Interestingly, manufacturer 10 is a major player in both the solution with the highest profit and the solution with the fewest GHG emissions. Manufacturer 10 is one of the closest steel processing manufacturers to the assembly center, limiting transportation emissions. In addition, manufacturer 10 also charges some of the lowest rates for steel milling of all manufacturers. Manufacturer 3 is always the only manufacturer chosen from Wisconsin, even though the distances between the clusters of manufacturers in Wisconsin and Illinois to the assembly center are similar. Electricity produced in Illinois has a significantly lower GHG emissions impact (0.39 kg CO_2/kWh) than Wisconsin (0.63 kg CO_2/kWh). This difference could explain why no other Wisconsin manufacturers are selected. Manufacturer 3 might also always be selected because it has more processing capabilities than any other manufacturer; it is the only manufacturer that can die cast the aluminum, mill it, and perform surface treatment all in-house. Manufacturers that can process the raw material to the final components are always preferred.

CONCLUSION

This work showcased new cyber-physical systems (CPS) technologies: the Operating System for Cyberphysical Manufacturing (OSCM) and the paired Network Operations Administration and Monitoring (NOAM) software. These technologies, and others like them, require new techniques to leverage their capabilities. With unprecedented communication and connection between designers and manufacturers possible with such technologies, more profitable production plans can be developed if objectives of all stakeholders are considered. Such technologies can also help quantify and manage environmental impacts of production plans. Thus, a mixed integer bilevel model based on the Stackelberg game was developed that considers the multiple objectives of designers and manufacturers in a manufacturing network connected with CPS technologies like OSCM and NOAM. The part designer (the leader) wished to produce their part(s) at maximum profit with minimum greenhouse gas (GHG) emissions. The manufacturers (followers) wished to minimize their costs while maximizing the uptime of their equipment. A decomposition-based solution algorithm leveraged the structure of the model to discretize the multi-objective solution space of the lower level problem.

The proposed model and solution algorithm were applied to a case study based on a network of manufacturers in Illinois and Wisconsin. The case study required components for at least 10,000 aluminum bearing brackets, rods, and steel gearbox housings. GHG emissions ranged from 2,152 kg CO_2-eq to 3,000 kg CO_2-eq with corresponding profits/losses of -$993,000 and $134,000. The approach found production plan alternatives with different profits and environmental impacts. The approach leveraged communication and connectivity advances provided by CPS to identify more profitable and environmentally friendly production plans. Thus, this work represents another step towards implementation of CPS at the manufacturing network level.

ACKNOWLEDGMENT

We gratefully acknowledge the financial support from the Presidential Fellowship program at Northwestern University, the National Science Foundation (NSF) Cyber-Physical Systems (CPS) under grant No. CPS/CMMI-1646592, and the Digital Manufacturing Design and Innovation Institute (DMDII). Special thanks also to Prof. Placid Matthew Ferreira and Marco Giovannini for advice and guidance on the project.

NOMENCLATURE

Decision variables and subset designations are denoted in upper case. All parameters are in lower case.

Sets and Subsets

f=f'	Set of all manufacturers in the manufacturing network
$FD \in f$	Subset of all final destinations (demand nodes)
m	Set of all input, intermediate, or final materials
n	Set of points found on each Pareto-optimal curve considered in the lower level
p	Set of all machining and manufacturing processes
$PM \in m$	Subset denoting all product materials

q	Set denoting number of divisions of each manufacturer's contract values
$RM \in m$	Subset of all raw materials
u	Set of points found on the upper level Pareto-optimal curve

Variables

$B_{ff'}$	Binary variable denoting if any material was transported from manufacturer f to destination f'
C_f	Contract/payment value to each manufacturer f from the leader in \$
FP_{fp}	Binary variable that determines if process p at manufacturer f is used or not
P_{mf}	Quantity of raw material $RM \in m$ purchased by manufacturer f in m^3
S_{mf}	Quantity of material m sent to final destination f in m^3
SL_{qn}	Binary variable denoting if the upper level selects the lower-level solution for division point q and corresponding Pareto-optimal point n
X_{pf}	Quantity produced by process p at manufacturer f in m^3

Parameters

ac_{fp}	Cost to run process p if process p is a surface area-based process
av_p	Area-to-volume ratio of the component to be processed in process p
ava_m	Availability of raw material $RM \in m$ in m^3
cfq_{fqn}	Optimal value of C_f at step q and Pareto-optimal point n from the lower level
cfn_f	Minimum feasible contract value for manufacturer f

cq_{fq}	Contract value for manufacturer *f* at step *q*
cfx_f	Maximum feasible contract value for manufacturer *f*
$d_{ff'}$	Distance in km from manufacturer *f* to destination *f'*
dc_f	Step size for range of contract values for manufacturer *f*
dem_m	Final demand of material *m* in m^3
dpe_{fp}	Direct GHG emissions from process *p* at manufacturer *f* in kg CO_2-eq/m^3
ε_n	Epsilon value for calculating point *n* along the lower level Pareto curve
ε_u	Epsilon value for calculating point *u* along the upper level Pareto curve
fc_{fp}	Fixed costs of process *p* at manufacturer *f*
fpp	Scaling parameter that ensures a minimum processing level of a process if it is selected
lc_{fp}	Cost to run process *p* if process *p* is a linear process
lv_{fp}	Linear processing requirement to volume ratio of the component to be processed in process *p*
mac_m	Cost of raw material $RM \in m$ in \$k/kg
md_{pm}	Negative parameter denoting if material *m* is consumed in process *p*
mp_{pm}	Positive parameter denoting if material *m* is produced through process *p*
mr_{fp}	Manufacturing rate of process *p* at manufacturer *f* in m^3/hr
ot	Overall time limit for the order to be filled in hours

pe_{fp}	Electricity consumption of process p at manufacturer f in kWh/m^3
pp_m	Selling price of final products $PM \in m$
ref_f	Regional electricity GHG emissions impact factor for manufacturer f in kg CO_2-eq/kWh
tc	Transportation cost in \$/m^3-km
td_{fqn}	Discretization of the time objective of the lower level for the ε-constraint method
te	Transportation emissions in kg CO_2-eq/km
$tr_{mff'qn}$	Optimal value of $TR_{mff'}$ at step q and lower level Pareto optimal point n
ts	Transportation speed in km/hr
vc_{fp}	Cost to run process p if process p is a volume-based process
xq_{fpqn}	Optimal value of X_{fp} at step q and lower level Pareto-optimal point n

Figure Captions List

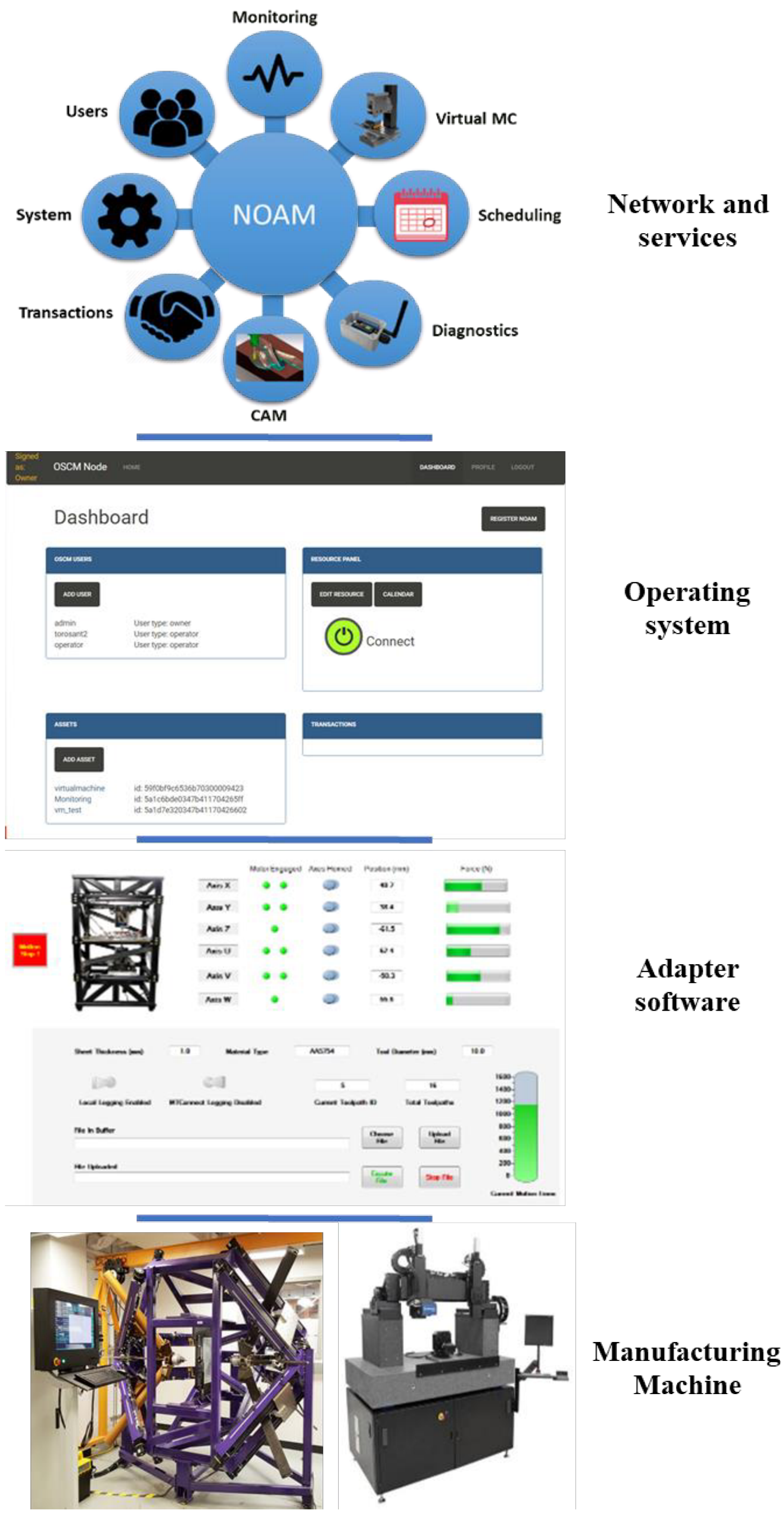

Figure 1. Cyber-physical manufacturing network framework: OSCM and NOAM

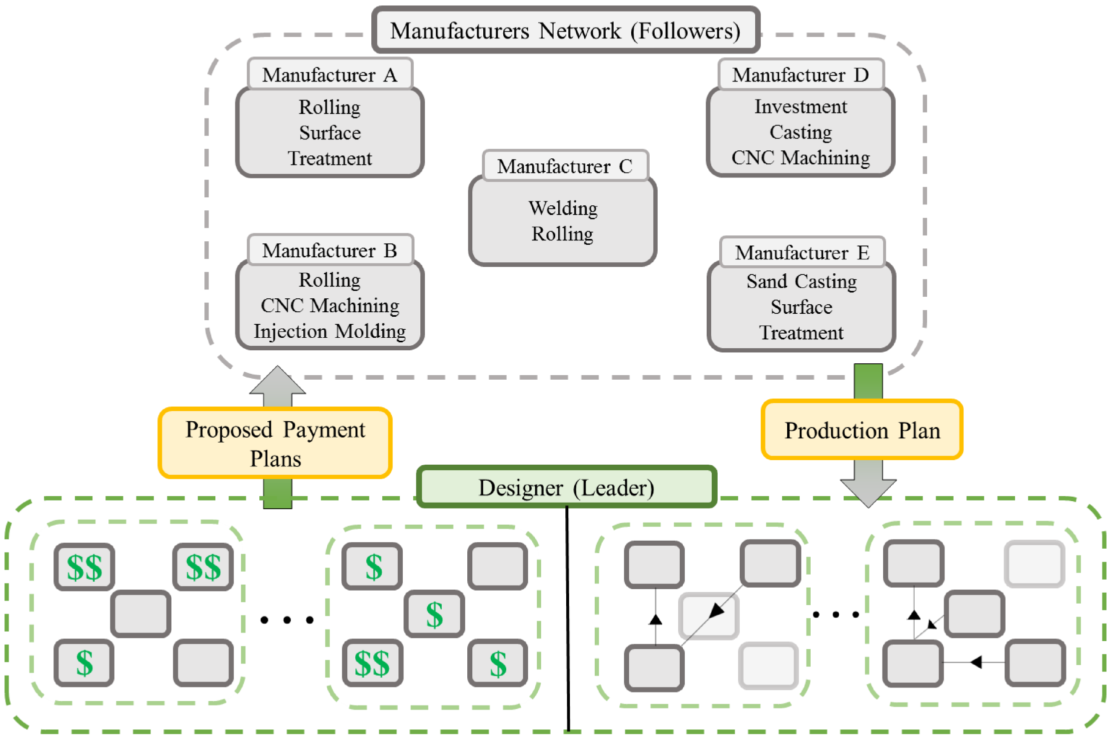

Figure 2. The designer (leader) proposes a set of payment distributions to the manufacturing network (followers). The manufacturers decide how to make the part under each payment distribution and return a manufacturing pathway to the designer.

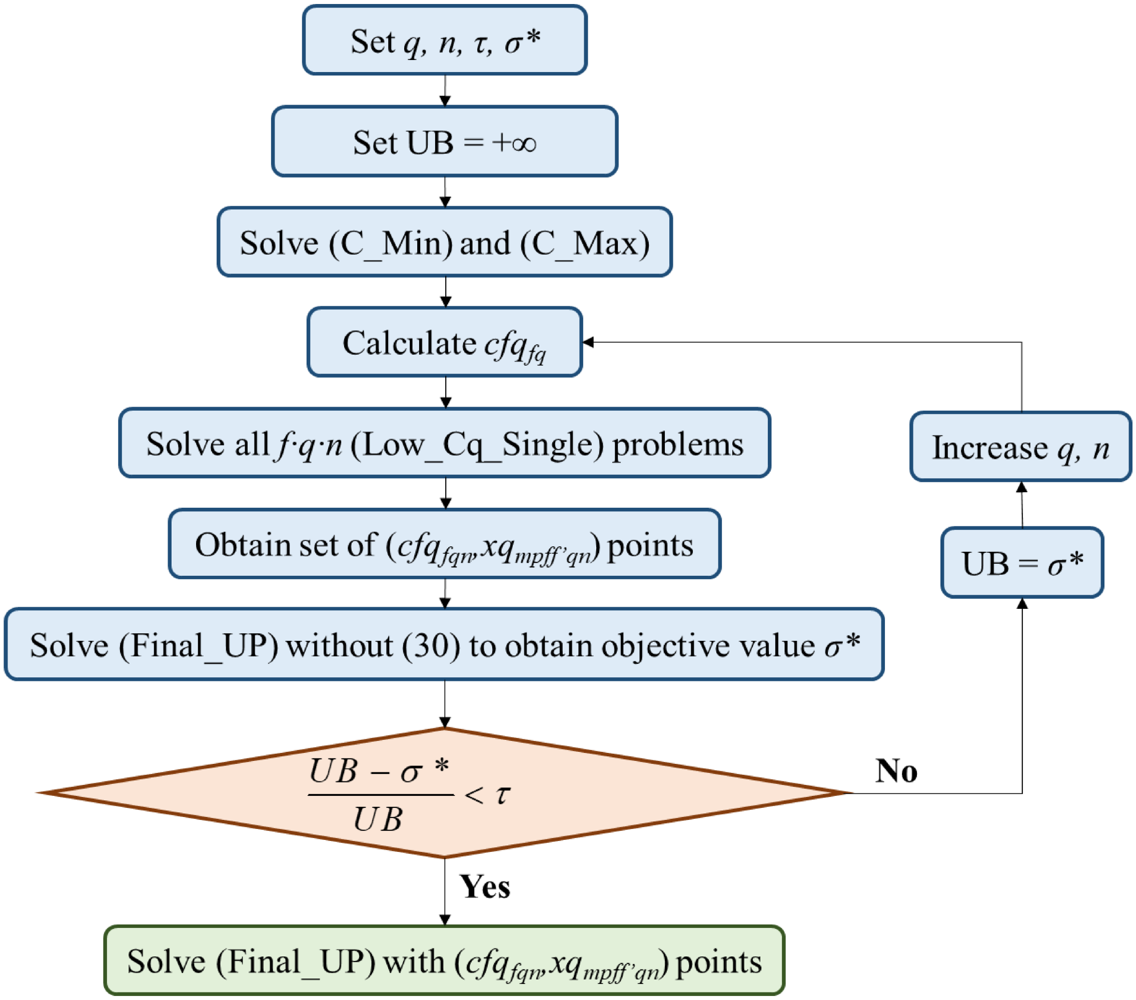

Figure 4. Solution algorithm flowchart.

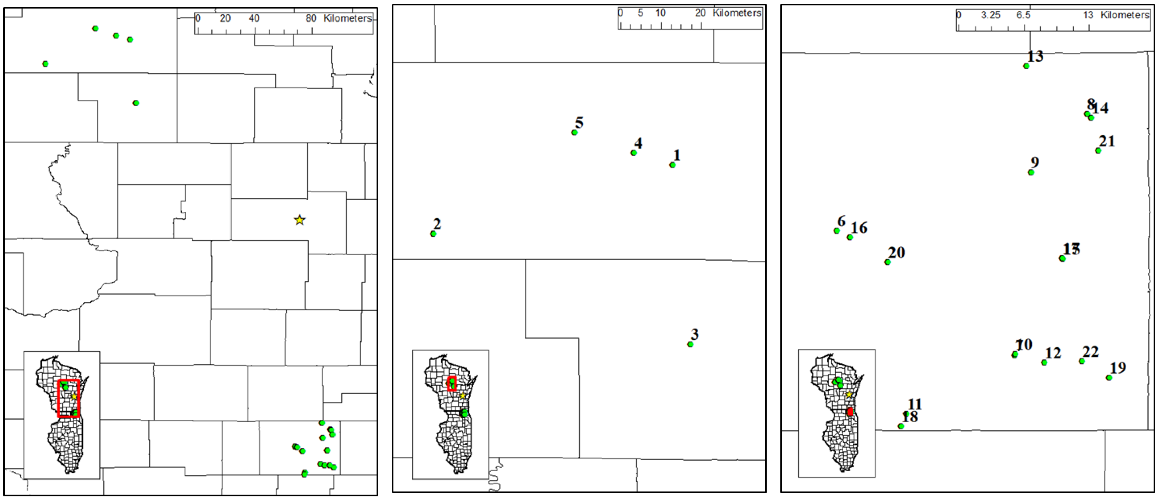

Figure 4. Maps representing the manufacturers (green dots) in Wisconsin and Illinois considered in the case studies. The yellow star is the final demand location. Full network (left), Wisconsin manufacturers (middle), and Illinois manufacturers (right). All map images created in ArcMap [84].

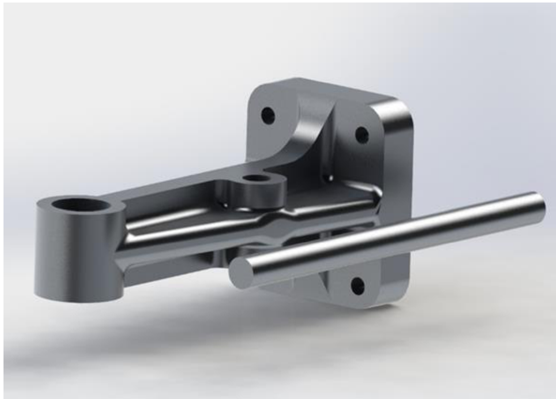

Figure 5. Part designs considered in the case studies. Aluminum bearing bracket (left), and steel gearbox housing (right).

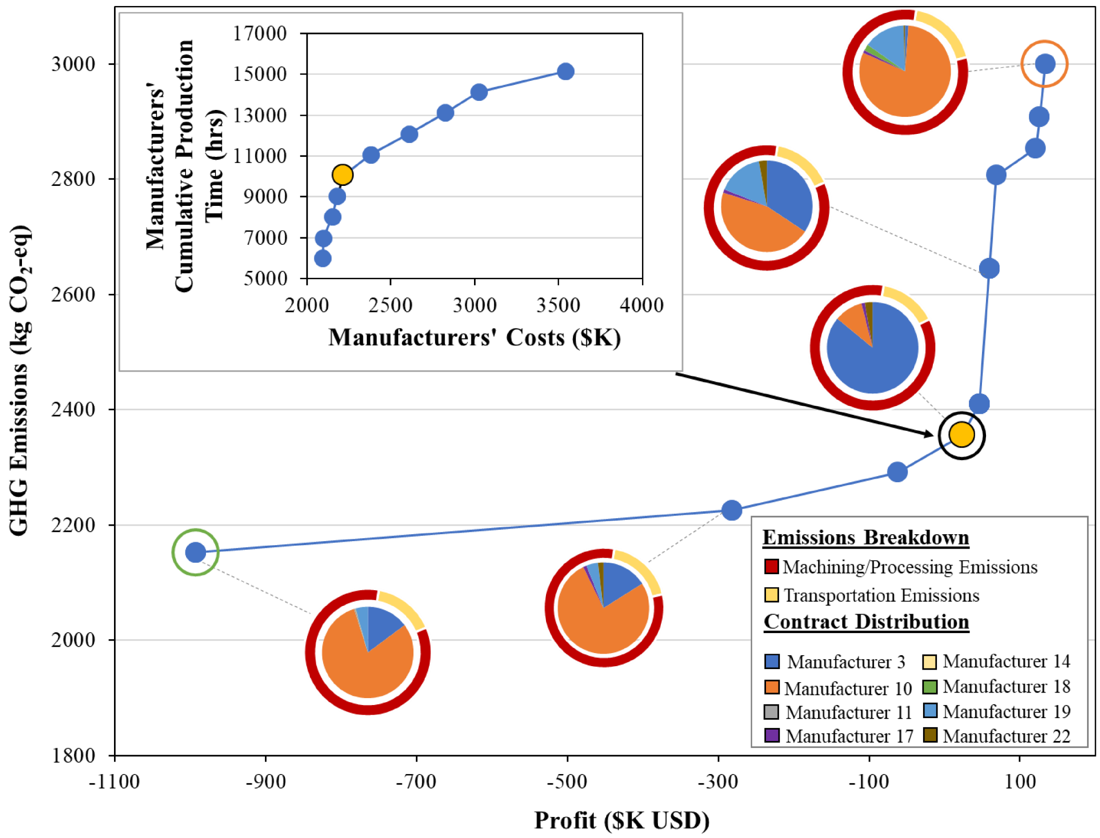

Figure 6. Case study results. The compromise solution is shown in yellow, and the corresponding Pareto-optimal curve for the manufacturers is also shown. The solution with the fewest GHG emissions is circled in green, and the solution with the highest profit is circled in amber.

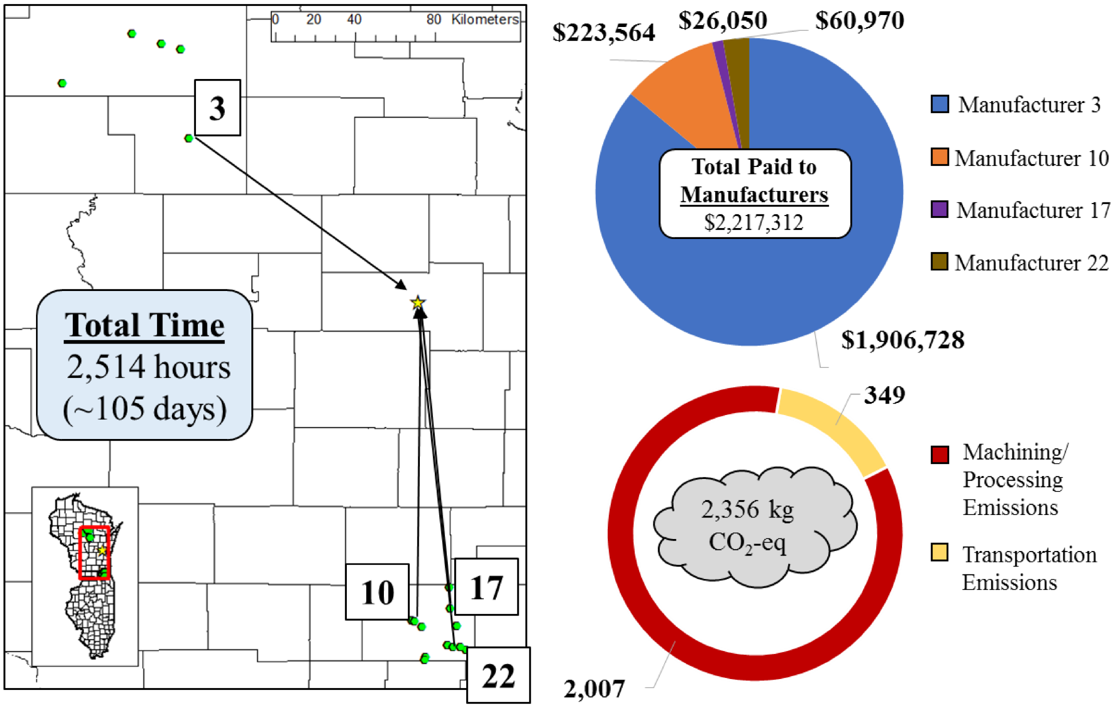

Figure 7. Production plan details for the compromise solution.

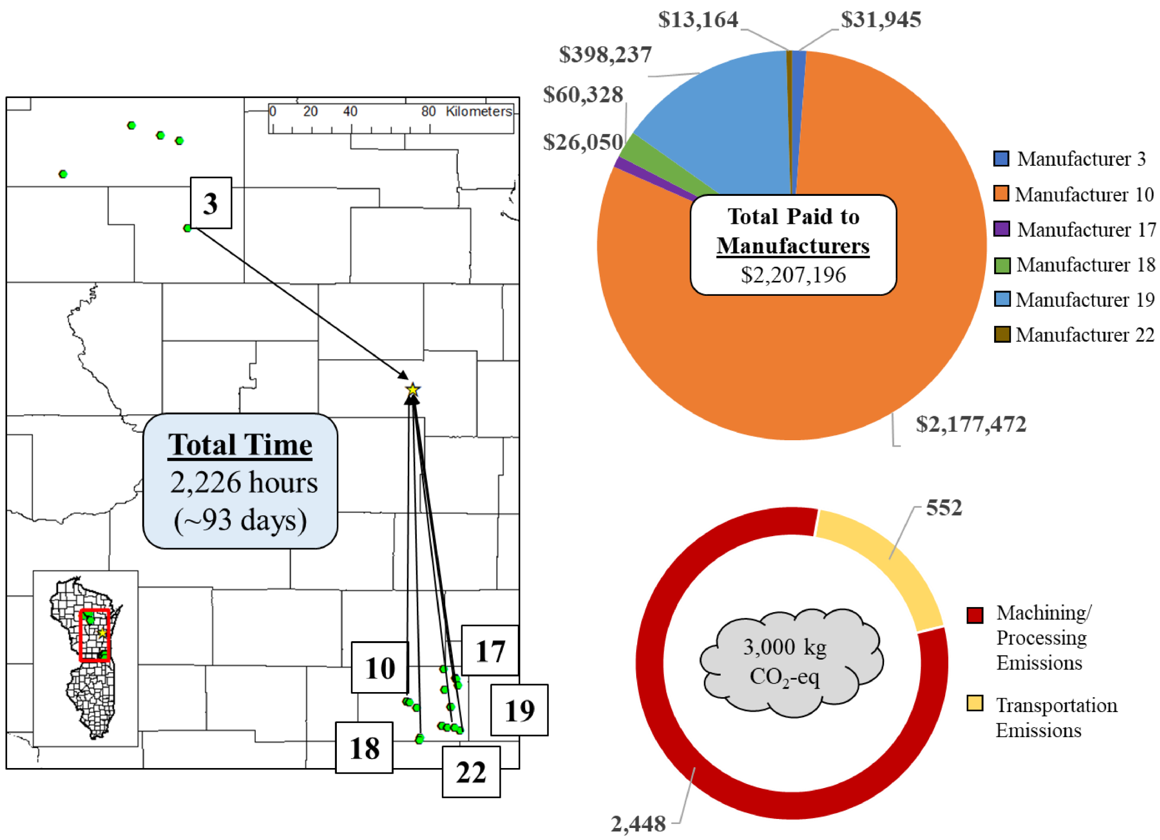

Figure 8. Production plan details for the solution with the highest profit.

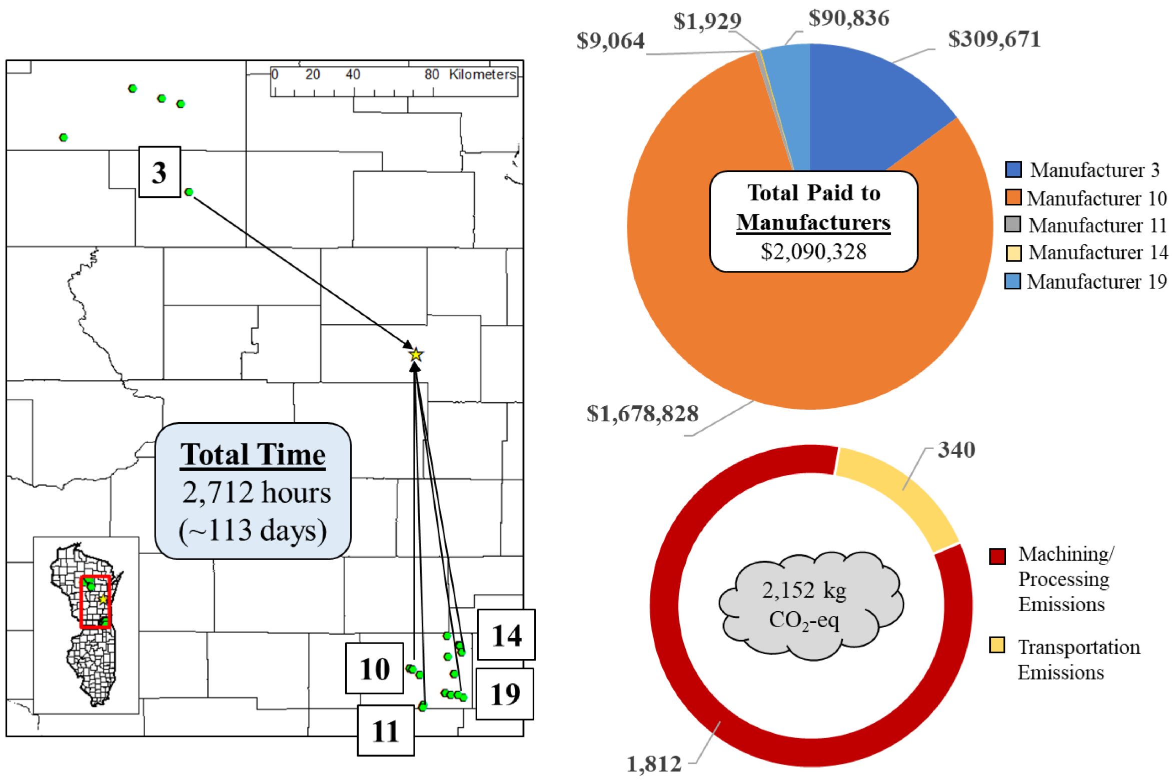

Figure 9. Production plan details for the solution with the fewest GHG emissions.

Table Caption List

Table 1. Parts, their components, required materials, and possible manufacturing sequence considered in the case study

Part	Component Name	Material	Manufacturing Sequence
Bearing Bracket	Bracket Body	Aluminum	Casting, Milling, Drilling, Painting
	Rod	Aluminum	Rolling
Gearbox Housing	Front Housing	Steel	Milling, Drilling, Painting
	Back Housing	Steel	Milling, Welding, Painting
	Rings	Polyethylene	Plastic Injection Molding

Table 2. List of manufacturers, their capabilities, and location by state

Manufacturer	Capabilities	State
1	Welding	WI
2	Rolling	WI
3	Drilling, Milling, Surface Treatment, Turning, Welding	WI
4	Surface Treatment	WI
5	Die Casting	WI
6	Surface Treatment, Welding	IL
7	Drilling, Milling, Rolling, Turning	IL
8	Drilling, Milling, Turning	IL
9	Surface Treatment, Welding	IL
10	Drilling, Milling, Welding, Surface Treatment, Turning	IL
11	Die Casting, rolling	IL
12	Sand Casting	IL
13	Welding	IL
14	Die Casting, Plastic Injection Molding	IL
15	Drilling, Milling, Turning	IL
16	Sand Casting	IL
17	Rolling	IL
18	Plastic Injection molding	IL
19	Sand Casting, Drilling, Turning, Surface Treatment	IL
20	Surface Treatment, Welding	IL
21	Drilling, Milling, Turning	IL
22	Drilling, Milling, Plastic Injection Molding, Turning	IL

Table 3. Production plan details for the compromise solution.

Manufacturer	Materials Purchased	Quantity Purchased (kg)	Processes	Products	Number Produced	Processing Time (hrs)
3	Aluminum Steel	4,023 19,240	**Al**: Die Casting, Milling, Drilling, Painting. **Steel**: Milling, Drilling, Welding, Painting	Aluminum Bracket Bodies Gearbox Back Housing Gearbox Front Housing	10,000 7,755 10,000	2,360 1,720 938
10	Steel	4,025	Milling, Welding, Painting	Gearbox Back Housing	2,245	417
17	Aluminum	6,777	Rolling	Aluminum Rods	28,784	2,510
22	Plastic Granules	3,320	Molding	Plastic Rings	316,000	1,107

Table 4. Production plan details for the solution with the highest profit

Manufacturer	Materials Purchased	Quantity Purchased (kg)	Processes	Products	Number Produced	Processing Time (hrs)
3	Aluminum	297	Die Casting, Milling, Drilling, Painting.	Aluminum Bracket Bodies	736	174
10	Steel	32,200	Milling, Welding, Painting	Gearbox Front Housing Gearbox Back Housing	10,045 15,014	525 2,220
17	Aluminum	6,777	Rolling	Aluminum Rods	28,784	628
18	Plastic Granules	3,280	Molding	Plastic Rings	312,381	1,640
19	Aluminum	3,753	Die Casting, Milling, Drilling, Painting	Aluminum Bracket Bodies	9,304	1,390
22	Plastic Granules	3,320	Molding	Plastic Rings	68,571	720

Table 5. Production plan details for the solution with the fewest GHG emissions

Manufacturer	Materials Purchased	Quantity Purchased (kg)	Processes	Products	Number Produced	Processing Time (hrs)
3	Aluminum	3,132	Turning, Drilling, Painting.	Aluminum Bracket Bodies	7,764	2,707
10	Steel	23,265	Milling, Drilling, Welding, Painting	Gearbox Front Housing Gearbox Back Housing	10,000 10,000	525 1,480
11	Aluminum	2,349	Rolling	Aluminum Rods	10,000	218
14	Plastic Granules	110	Molding	Plastic Rings	10,476	22
19	Aluminum	891	Die Casting, Milling, Drilling, Painting	Aluminum Bracket Bodies	2,209	330

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