Assessment of Sustainability Tradeoffs in Renewable Energy Generation and Additive Manufacturing

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Amir T. Namin

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ABSTRACT

Renewable energy generation and additive manufacturing are becoming more widespread, in part because of their sustainability benefits, where sustainability is measured by its environmental, economic and social attributes. The first part of the dissertation explores the economic and environmental tradeoffs of using energy generated by onsite roof-mounted high efficiency solar panels to power manufacturing facilities. The System Advisor Model (SAM) was used to investigate viability of solar irradiance for facilities across all of the industrial sectors in all U.S. states using the Manufacturing Energy Consumption Survey (MECS) database. Five case studies further explore the economic feasibility and environmental implications of installing onsite roof-mounted high efficiency solar PV systems for industrial facilities in five select U.S. states (California, Florida, Indiana, New Jersey, and Texas), which have varying levels of solar irradiance, different incentives, and solar policies. Results indicate that lower Levelized Cost of Energy (LCOE) and positive Net Present Value (NPV) can be achieved under certain conditions with the economic payback time ranging from 3 to 15 years. Energy Pay Back Time (EPBT) could
be less than two years for the five select states with the CO2 equivalent abatement cost ranging from $0.5 - $151 per ton.

In the second part of the dissertation, economic and social attributes are investigated for the adoption dynamics of metal 3D printed customized (individually-made) medical implants. The study uses system dynamics simulation modeling to characterize the impact of barriers such as insurance policy coverage, and physicians’ preferences on the adoption of customized hip and knee implants. The findings indicate that these products can be more cost effective than off-the-shelf implants because of reduction in readmissions, revision surgeries, and recovery duration. Custom implants can also improve patients’ quality of life by providing more comfort and better performance. Hence, customized hip and knee implants appear to be more sustainable in the long-term. Distributed additive manufacturing of hip and knee implants onsite within hospitals in Massachusetts can further reduce adverse impacts on environment when powered by onsite solar PVs. Finally, a multi objective facility location allocation problem is modeled as a Mixed Integer Programing (MIP) to determine the optimal number of additive manufacturing centers, their location, and product flow in the network under different demand scenarios. These studies indicate that the adoption of distributed additive manufacturing for personalized healthcare would lead to greater sustainable development.
Dedicated to my parents,

Naghmeh and Mahmoud
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Chapter 1 -
Introduction

The wish for achieving sustainable advancement has never been preeminent before. In 2014, the President’s Council of Advisors on Science and Technology (PCAST), reported the advanced manufacturing partnership committee with the aim to accelerate U.S. advanced manufacturing (PCAST 2014). The report indicated that the advanced manufacturing technologies progress including new energy resources, new material processes, energy grid, and 3D printing/Additive Manufacturing (AM), should significantly improve product customization and value, dynamic performance and innovation. According to the report, smart manufacturing can be considered as a dynamic model-based decision-making system for all aspects of manufacturing operations that can lead to improve the flexibility of our plants, optimization, sustainability, and quality. Four key trends of smart manufacturing and supply chain are: 3D printing/AM, distributed manufacturing, demand driven supply chain, and Internet of Things (IoT) driven analytics. Former secretary of energy Dr. Ernest Moniz described smart manufacturing as “a key information
technology approach to unlocking energy efficiency in manufacturing.” Modern manufacturing industries are energy and resource intensive, and a substantial contributor to greenhouse gas emissions (Panwar, Kaushik et al. 2011, Sangwan, Herrmann et al. 2018); therefore, utilizing clean energy resources, improve manufacturing technology and use lower impact materials are three basic strategies for cleaner production and green manufacturing discussed by (Dornfeld 2009, Zhang and Dornfeld 2010, Dornfeld 2014). Potential sustainability benefits of AM can be categorized to: improving resource efficiency; reconfiguring value chain (shorter and simpler supply chain); eliminating production steps; supporting distributed manufacturing at the point of use (Ford and Despeisse 2016).

The phenomenon of adoption and diffusion of new technologies have been widely studied in several areas. This dissertation analytically explores the adoption of emerging technologies in manufacturing and the interconnection among the three pillars of sustainability which play a crucial role in sustainable decision making considering economic, social and environmental impacts of the emerging technologies.

1-1. Research Objectives

Energy use in the industrial sector is highly heterogeneous, therefore, policy design and energy consumption modeling in the industrial sector is quite challenging (Karali 2012, Fais, Sabio et al. 2016). Renewable energy resources such as wind and solar technologies that, are becoming more prevalent because of their economic, environmental, and societal advantages, could provide more sustainable energy generation. Furthermore, advanced manufacturing technologies such as medical 3D printing is gaining momentum. These technologies not only can improve process
efficiency and sustainability, but also can provide high quality customized products. In medical area, distributed 3D printing has already revolutionized the treatment processes with tremendous potential yet to be realized (Chepelev, Giannopoulos et al. 2017). The adoption of the renewable energy technologies along with distributed additive manufacturing is expected to be more pervasive.

The first objective of this research is to support sustainable manufacturing by employing an energy simulation tool for policy analysis to assess the feasibility of utilizing high efficiency solar PVs as an alternative source for energy generation for the industrial sectors in the U.S. The second objective is to develop dynamic simulation model for policy analysis to investigate the adoption dynamics and long-term effects of using 3D printing technologies to fabricate customized individually made medical implants. The final objective is to utilize optimization methods, mixed integer programing (MIP) specifically, to analyze and characterize the performance of facility location allocation model to support distributed additive manufacturing/3D printing to fabricate customized individually made medical implants.

1-2. Summary of Research Contributions

The contributions of this work are summarized as follows:

1. A novel analysis is provided for adoption of high efficiency roof-mounted solar PVs for the industrial sector which, generally have steady load profile and flat large roof areas, for onsite energy generation. The analysis allows manufacturers and policy makers to assess the suitability of the U.S. states for various industrial sectors in the
U.S. for energy generation from renewable solar. We integrate an energy simulation environment to explore the effects of locational based conditions such as financial incentives, regulatory policies, and weather profile on economic and environmental pillars of sustainability in five U.S. states.

2. A dynamic simulation model is developed to explore the long term impacts of using 3D printed customized individually made hip and knee implants on patients’ wellbeing and economic satisfaction of the stakeholders. In this chapter, the economic and social pillars of sustainability are compared for the customized individually made and conventional implants. For this purpose, we articulate the problem, model the customized individually made implants diffusion and formulate a feedback dynamic flow structure by utilizing system dynamics simulation modeling to evaluate the economic and social impacts of the new products to help decision and policy makers to come up with appropriate policies.

3. An optimization model is developed to explore the flexibility of distributed 3D printing for customized individually made implants fabrication onsite of hospitals in the state of Massachusetts. By integrating the mixed integer programming optimization model, rather than prioritizing one objective over the other, we explore the contradictory nature of the system level costs and distance priorities of utilizing the new technologies for customized individually made implants production to fulfil the required demand of these products under various demand scenarios in the state of Massachusetts.
1-3. Outline

The remainder of this dissertation is as follows:

Chapter 2 express a novel developed framework to evaluate the potentials and suitability of each state for renewable solar energy generation considering all the industrial sectors available in the U.S. System Advisor Model (SAM) as an energy simulation modeling tool is integrated to explore each state feasibility in adopting roof-mounted high efficiency solar PVs for manufacturing facilities. Furthermore, the simulation model is used to estimate economic and environmental potentials of high efficiency solar PVs adoption in five different states as a case study. The outcome of the model indicates that, according to the geographical location of each state, the lowest and highest electricity generation from high efficiency roof-mounted solar PVs can meet 100% of the required energy for 19% and 57% of industrial sectors respectively. Additionally, 48% of the industrial sectors can rely on the high efficiency solar PVs to cover 100% of their demands regardless of the location. Finally, the results of the case study illustrate great potentials in economic and environmental feasibility of the high efficiency roof-mounted solar PVs in locations that are not always obvious sunny locales.

Chapter 3 describes a dynamic simulation model to investigate the adoption dynamics of the 3D printed customized individually made implants. The system dynamics model is integrated to compare the patient outcome and satisfaction as well as the long-term economics of customized and conventional hip and knee implants. Furthermore, the barriers on the adoption of customized individually made implants such as no long-term proven evidence that customized implants can directly improve patient outcomes; surgeons preference of conventional implants because of their
training, familiarity, and comfort level with those products; potential increased malpractice liability insurance costs and legal risks due to ordering and administrative issues; because of the higher cost of customized individually made implants, the third-party payers do not provide coverage for those procedures, and etc. are explored in this chapter. The outcome of the model indicates that, by 2026, an adoption rate of 90% for customized individually made implants can reduce the number of readmissions and revision surgeries by 62% and 39%, respectively, and can save hospitals and surgeons 6% on procedure time, and cut down cumulative healthcare costs by approximately $38 billion.

Chapter 4 presents a facility location allocation optimization model to provide helpful insights for decision makers to utilize 3D printing for customized individually made implants fabrication onsite of the hospitals in the state of Massachusetts. In this chapter, mixed integer programming (MIP) is used to model customized individually made implants (hip and knee) relative production cost to conventional implants, transportation cost, lead time cost and weighted distance penalty for several demand scenarios. According to the decision makers’ preferences, the model provides several locations to establish AM centers onsite of hospitals as well as the assignment of the demand nodes (hospitals without AM center) to the AM facilities. The model also decides on the production volume and flow of each type of the products in the network. The outcome of the model delivers meaningful insights for decision makers over a range of preferences which could support customized individually made implants production and adoption in the state of Massachusetts and beyond.
Chapter 2 -
Comparative analysis of economic and environmental tradeoffs of renewable solar energy for industrial sector in US: case study of high efficiency roof-mounted solar plants for five manufacturing locations

Manufacturing activities is responsible for approximately one-third of primary energy use and greenhouse gas emissions globally. As the interest in renewable energy, specifically wind and solar, is growing, this chapter explores the potentials of each U.S. state in generating electricity from high efficiency solar PVs for the industrial sectors onsite of the manufacturing facilities. The suitability of each state in terms of required electricity coverage for the industrial sectors from high efficiency renewable solar PVs is assessed by analyzing the Manufacturing Energy Consumption Survey (MECS) database on net energy demand and average enclosed floor space for all industrial sectors and integrating an energy simulation modeling tool (system advisor model- SAM). Additionally, this chapter considers the economic feasibility and environmental implications of
installing onsite roof-mounted solar PV systems on a case study manufacturing facility in five U.S. states (California, Florida, Indiana, New Jersey, and Texas), which have varying levels of solar irradiance, different incentives, solar policies, and manufacturing incentives at both the federal and state level. In these five cases, a combination of high efficiency SunPower solar panels (monocrystalline) with sun tracking technology are considered. Using NREL’s System Adviser Model (SAM), common financial metrics such as the economic payback period, Net Present Value (NPV), Levelized Cost of Energy (LCOE), and price of CO₂ equivalent abatement are investigated considering the federal and local incentive policies for the selected states. Energy Pay Back Time (EPBT) and Greenhouse Gas emissions (GHG) as common environmental performance metrics for life cycle of PVs are compared for different cases. The results indicate, lower LCOE and positive NPV can be achieved under certain conditions with the economic payback time ranging from 3 to 15 years. EPBT is less than two years for the five selected states with the CO₂ equivalent abatement cost ranging from $0.5 - $151 per ton.
2-1. Introduction

The industrial sector is a significant source of global primary energy consumption and GHG emissions at 33% and 37% globally (International-Energy-Agency 2017). In the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC), industrial sector was reported as the top pollutant end-use sector (Allen, Barros et al. 2014). For Organization for Economic Cooperation and Development (OECD) countries, manufacturing contributes on average 16% of Gross Domestic Product (GDP), increasing to more than 30% for China and South Korea (Cerdas, Juraschek et al. 2017, WorldBank 2017). The first “technology roadmap” for renewable energy in manufacturing as part of REmap 2030 reported by International Renewable Agency (IRENA 2014), illustrates that renewable energy could grow to 27% of total global energy consumption for industrial sector by 2030; however, in the U.S., only 1.5% of the required electricity by the industrial sector was generated onsite through renewable sources other than biomass (DOE 2010). Nationally determined contributions (NDCs), as heart of the Paris agreement, include emissions reduction pledges by each country and adaptation to the impacts of climate change (UN 2015). After the Paris agreement, a broad range of manufacturing firms engaged in voluntary climate actions to meet GHG reduction targets (Hsueh 2015). On aggregate, by full implementation of NDCs, it is expected to limit the global emissions level below 2°C warming; however, the current industrial sector situation indicates significant insufficiency to set the global warming limit of 2°C (Boyd, Turner et al. 2015, Olhoff, Christensen et al. 2015, UN 2015, Dietz, Fruitiere et al. 2018). One of the major contributors to greenhouse gas emissions is fossil fuel-based electricity generation. Hence, a key climate action has been for businesses for transition to the distributed or onsite electricity generation from renewable sources. Distributed
renewable energy generation can deliver strategic advantages not only for GHG emissions reduction from fossil fuel-based electricity generation but also in improving reliability of power sources with lower possibility of disruptions or blackouts, and economic feasibility by decreasing energy costs and possibility of selling surplus power to utility companies; and enhanced brand reputation (Polaris 2014, Penndorf 2016, EPA 2018). Level of maturity in climate and energy management, economic feasibility, availability, and flexibility of renewables could play a significant role in the adoption of renewable energies (IRENA 2018).

There is a growing demand for renewable energy among major U.S. manufacturers (Danigelis 2017), nevertheless, the industrial sector was responsible for 22% of GHG emissions in 2016 (EPA 2018). The report indicated that 25% and 83% of the 160 largest manufacturers initiated renewable energy goals and GHG reduction targets respectively. Renewable electricity is traced by 49% of companies in the U.S. Among the 25 largest renewable electricity consumers, excluding materials sector, just 6% belongs to self-generation whereas 50%, 25%, 14%, and 5% pertain to energy attribute certificate (EAC), corporate power purchase agreement (PPA), utility contracts, and others respectively. Michigan, Missouri, North Carolina, and Tennessee are in the top 10 U.S. states in terms of number of manufacturing facilities, while in the bottom 25 in the renewable energy friendliness for corporations (Danigelis 2017). Figure 2-1a illustrates statewide GHG emissions and energy consumption by industrial sector in 2016 (EIA 2018). Indiana, Pennsylvania, California, Louisiana, and Texas are the top 5 states with the highest GHG emissions and energy consumption from manufacturing (EIA 2018). More information on the statewide industrial sector GHG emissions are presented in Figure 2-1b.
Wind and solar energy technologies are becoming more widespread among the other renewable sources because of rapidly falling cost factors, efficiency improvement and flexibility (Trancik, Jean et al. 2015, LAZARD 2017). The agreement between Xcel Energy and steelmaker EVRAZ in Colorado for a 240 MW solar project (Roselund 2018), the World’s largest lithium ion battery factory, Tesla’s Gigafactory (TESLA 2018), and General Motors’ contract for a 200 MW
wind energy in Illinois and Ohio for manufacturing facilities (Danigelis 2017) can illustrate manufacturers’ motivation toward wind and solar renewables. Levelized Cost of Energy (LCOE) values have been continuously falling for renewable energy technologies in the past years. The decrease is quite significant, such that in some cases the building and operating costs of new renewable energy projects have decreased below the operating costs of existing conventional electricity generation technologies such as coal or nuclear (LAZARD 2017). This chapter initiates an assessment of the potentials of solar PVs to be used by the industrial sector for onsite energy generation for the manufacturing facilities. The aim is to provide a systematic overview that allows manufacturers and policy makers to assess the suitability of the U.S. states for different industrial sectors available in the country in terms of renewable solar energy generation.

MECS data (EIA 2014) is mined to determine the electricity demand intensity ranges of kW/m² for 20 3-digit industry subsectors according to the North American Industry Classification System (NAICS)(Census-Bureau 2017). MECS is a national sample survey reported by Environmental Investigation Agency (EIA) that includes U.S. manufacturing establishment information, their energy related building characteristics and energy consumption and expenditures which represents 97-98% of the U.S. manufacturers (EIA 2014). NAICS is the standard used by Federal statistical agencies for classifying and analyzing the U.S. business establishments (Census-Bureau 2017). Furthermore, this chapter explores the economic and environmental impacts of utilizing roof-mounted solar PV systems on manufacturing facilities in five U.S. states (California, Florida, Indiana, New Jersey, and Texas) as a case study. These states were chosen to represent a range of solar irradiance, solar policies, and manufacturing incentives. In these five cases, a combination of high efficiency SunPower solar panels (monocrystalline) with
sun tracking technology are considered. Specifically, the generalizable contributions of this work include:

- A novel framework with the focus on how plausible onsite energy generation from renewable solar resource is for U.S. manufacturers in general and which combination of states and industry sectors would be more suitable when the manufacturers consider solar PV as an alternative source for energy generation.
- The analysis to support sustainable manufacturing by providing helpful insights for policymakers and manufacturers to facilitate the transition to renewable solar energy.
- The demonstration of a comparative policy analysis to investigate the influence of state incentives and regulatory policies, as well as physical and locational differences, on the economic and environmental performance of high efficiency monocrystalline solar PV panels used for powering manufacturing processes.

The rest of this chapter is organized as follows: Section 2-2 includes model development, background information on the case study and model descriptions and parameters; Section 2-3 provides the results; Section 2-4 illustrates the sensitivity analysis for the case study; Section 2-5 contains the discussion, conclusion and potential future work.

2-2. Model development

In this study, Manufacturing Energy Consumption Survey (MECS)(EIA 2014) database is mined to estimate electricity demand intensity defined as net electricity demand per unit area per year, for all the 20 3-digit North American Industry Classification System (NAICS) subsectors (Census-Bureau 2017) in the U.S. to compare all the states for their potentials of generating onsite
electricity required for the manufacturing facilities. Electricity demand intensity can be determined according to MECS database by dividing the net energy demand of each of the establishments of a sector by average enclosed floor space per establishment (EIA 2014). Solar electricity generation per unit area per year are calculated by using the System Advisor Model (SAM)(NREL 2016) to compare the possibilities for energy generation from onsite roof-mounted panels in all the U.S. states with the electricity demand intensity of the industrial subsectors. SAM was developed by the National Renewable Energy Laboratory (NREL) in collaboration with Sandia National Laboratories in 2005 for internal use of the U.S. Department of Energy (DOE) for solar energy technologies program and analysis. The first public version was released by NREL in 2007. After 2007, NREL continued to release one or two new versions each year with periodic maintenance and updates as needed (Blair, Dobos et al. 2014). SAM can be categorized into the techno-economic energy simulation model which can provide helpful insights for decision makers in the renewable energy industry.

The input data are the performance characteristics of physical equipment, project cost and financial assumption. NREL’s National Solar Radiation Database for solar resource data and ambient weather conditions is integrated into SAM performance models, that uses Typical Meteorological Year 3 (TMY3) as one option for weather data, which is used in this study (NREL 2014). The module and inverter parameters provided by SAM in several libraries as performance data and characteristics of available system components are in compliance with the California Energy Commission (CEC) report (Aldrich, Garfield-Jones et al. 2015). The performance model runs based on hourly or sub hourly time step simulation to calculate the system’s output in a year. In the present study, high efficiency monocrystalline solar panels manufactured by SunPower
(SPR-X22-470-COM) with 22% nominal efficiency, maximum power of 476 (Wdc) and 0.36% degradation rate are used to determine the potentials for generating onsite solar energy (NREL 2012, Gul, Kotak et al. 2016, SunPower 2017). Since the energy production and efficiency of solar PVs can be increased by 12%-20% when using sun tracking systems (Al-Mohamad 2004, Lazaroiu, Longo et al. 2015), two-axis tracking solar systems are considered in the installation. An inverter manufactured by ABB (TRIO-20.0-TL-OUTD-S1B-US-480-A) with 97.5% CEC weighted efficiency, maximum AC power of 20000 (Wac) and maximum MPPT DC voltage of 800 (Vdc) which can provide actual DC to AC ratio of 1.20 is used in this study (ABB 2014).

2-2.1. Case Study

The case study explores the economic and environmental impacts of utilizing high efficiency roof-mounted monocrystalline solar system discussed previously in five U.S. states (California, Florida, Indiana, New Jersey, and Texas) for a lithium-ion battery manufacturing facility with a detailed production model presented by (Hakimian, Kamarthi et al. 2015). The facility houses equipment for different processes (e.g., cathode and anode material mixing, calendaring/pressing, wetting/filling, forming, and testing). The total floor space required to fabricate the final product should be a minimum of 8,000 m² according to (Hakimian, Kamarthi et al. 2015). This value is close to the average enclosed floor space per establishment of ~8,500 m² for facilities under North American Industry Classification System (NAICS) code 335xxx “electrical equipment, appliance and components” sector reported by Energy Information Administration (EIA) (EIA 2014). The plant is designed to produce 1 million batteries, with a net electricity requirement of approximately 4.5 kWh per battery, which results in electricity demand
of 4.5 GWh per year (Hakimian, Kamarthi et al. 2015). According to the solar module and the available roof area, the manufacturer can accommodate mounting of approximately 3668 modules with desired array size of 1.75-MW, determined by (SAM-Version 17.9.5). The rated capacity is the same for the states of interest, because the identical type of solar PV panels is considered to be utilized on an equivalent roof area of a battery manufacturing facility in each state as presented in Table 2-1.

Table 2-1: Solar PV System Information

<table>
<thead>
<tr>
<th>State</th>
<th>System Nameplate (MW)</th>
<th>Capacity Factor (%)</th>
<th>Specific Location</th>
<th>Annual Average Irradiance (kWh/m²/day) (NREL 2016)</th>
<th>1st yr Generation (MWh)</th>
<th>1st yr Demand Coverage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>California</td>
<td>1.75</td>
<td>26.0</td>
<td>San Jose</td>
<td>6.5-8</td>
<td>3980</td>
<td>88</td>
</tr>
<tr>
<td>Florida</td>
<td>1.75</td>
<td>22.3</td>
<td>Miami</td>
<td>5-5.5</td>
<td>3407</td>
<td>76</td>
</tr>
<tr>
<td>Indiana</td>
<td>1.75</td>
<td>20.7</td>
<td>Indianapolis</td>
<td>4-4.5</td>
<td>3175</td>
<td>70</td>
</tr>
<tr>
<td>New Jersey</td>
<td>1.75</td>
<td>20.1</td>
<td>Newark</td>
<td>4-4.5</td>
<td>3084</td>
<td>69</td>
</tr>
<tr>
<td>Texas</td>
<td>1.75</td>
<td>24.3</td>
<td>Dallas</td>
<td>5.5-7</td>
<td>3728</td>
<td>83</td>
</tr>
</tbody>
</table>

Each location is simulated using SAM (NREL 2016) to assess the long-term economic and environmental tradeoffs of operating a 1.75-MW solar plant with high efficiency monocrystalline roof-mounted panels for 25 years. The economic analysis considers net present value (NPV), LCOE, economic payback period, and price of GHG emissions abatement per metric ton of CO₂ equivalent. Many of the larger manufacturing firms have set greenhouse gas emissions reduction targets in regions with qualified carbon emissions trading schemes. Such firms typically
evaluate and compare the costs of reducing GHG emissions through different abatement options, using metrics such as the price per ton of CO$_2$ equivalent emissions abated. The environmental benefits of using onsite renewable electricity as opposed to grid electricity, are explored for reductions in GHG emissions along with nitrogen oxide (NO$_x$) and sulfur dioxide (SO$_2$) cumulative emissions. Furthermore, the Cumulative Energy Demand (CED) and expected output of each PV system is used to determine the Energy Payback Time (EPBT) for each location.

2-2.2. Model description and parameters

The model simulates changes under availability or absence of financial incentives and regulatory policies from 2018 for 25 years, which can be expanded for trajectories beyond the studied period. Figure 2-2 presents a flowchart of the model. Its inputs are cost factors such as module, inverter, Balance of System (BOS), general information including weather data, electric load, system loss, and financial parameters such as tax and insurance rates, incentives and regulations. The outputs of the model are economic factors (NPV, LCOE and economic payback period) and environmental impacts (EPBT, CO$_2$ equivalent abatement, and air emissions avoided).
PV module efficiency plays an important role in project economics and energy payback time because high efficiency panels can reduce the number of PV modules and associated equipment including the foundation and cables (Ito, Kato et al. 2008). Electricity price escalation rates are considered according to the average annual increase in retail price of electricity for industrial sector from 2001 to 2017 in the selected states (EIA 2018). The five selected states cover a rating, by an industry organization evaluating state incentives for solar grades, ranging from A to C (DSIRE 2018, Wavesolar 2018). Additionally, the percentage of total state gross products from manufacturing ranges from 5% to 30% for Florida, New Jersey, California, Texas, and Indiana, respectively (NAM 2018). Detailed information for each state including state business incentives and solar friendliness is presented in Table 2-2.
Table 2-2: Background information on manufacturing importance and solar energy friendliness for the five states of interest.

<table>
<thead>
<tr>
<th></th>
<th>California</th>
<th>Florida</th>
<th>Indiana</th>
<th>New Jersey</th>
<th>Texas</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP from mfg [Billion $]</td>
<td>305</td>
<td>48</td>
<td>106</td>
<td>41</td>
<td>246</td>
<td>(NAM 2018)</td>
</tr>
<tr>
<td>% of total state products from mfg</td>
<td>11.1%</td>
<td>5%</td>
<td>29.5%</td>
<td>8.5%</td>
<td>14.5%</td>
<td>(NAM 2018)</td>
</tr>
<tr>
<td>No. of mfg firms</td>
<td>36117</td>
<td>12367</td>
<td>7102</td>
<td>7100</td>
<td>17594</td>
<td>(NAM 2018)</td>
</tr>
<tr>
<td>No. of mfg firms</td>
<td>1284</td>
<td>345</td>
<td>517</td>
<td>241</td>
<td>848</td>
<td>(NAM 2018)</td>
</tr>
<tr>
<td>Business Tax climate index ranking</td>
<td>48</td>
<td>4</td>
<td>9</td>
<td>50</td>
<td>13</td>
<td>(TAX-FOUNDATION 2018)</td>
</tr>
<tr>
<td>Corporate Tax ranking</td>
<td>32</td>
<td>19</td>
<td>23</td>
<td>42</td>
<td>49</td>
<td>(TAX-FOUNDATION 2018)</td>
</tr>
<tr>
<td>Cost of doing business ranking</td>
<td>49</td>
<td>31</td>
<td>1</td>
<td>43</td>
<td>21</td>
<td>(Cohn 2015)</td>
</tr>
<tr>
<td>Eco-friendly behavior ranking</td>
<td>4</td>
<td>26</td>
<td>42</td>
<td>13</td>
<td>37</td>
<td>(Kiernan 2018)</td>
</tr>
<tr>
<td>Overall solar grade</td>
<td>B</td>
<td>C</td>
<td>C</td>
<td>A</td>
<td>C</td>
<td>(DSIRE 2018, Wavesolar 2018)</td>
</tr>
<tr>
<td>RPS grade (renewable portfolio standards)</td>
<td>A</td>
<td>F</td>
<td>D</td>
<td>B</td>
<td>D</td>
<td>(DSIRE 2018, Wavesolar 2018)</td>
</tr>
<tr>
<td>Net metering grade</td>
<td>A</td>
<td>A</td>
<td>B</td>
<td>A</td>
<td>D</td>
<td>(DSIRE 2018, Wavesolar 2018)</td>
</tr>
<tr>
<td>Net metering value</td>
<td>Monthly total excess credited to next month bill in $ at sell rates</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(DSIRE 2018)</td>
</tr>
<tr>
<td>Interconnection grade</td>
<td>A</td>
<td>D</td>
<td>B</td>
<td>A</td>
<td>D</td>
<td>(DSIRE 2018, Wavesolar 2018)</td>
</tr>
<tr>
<td>Interconnection value</td>
<td>$800</td>
<td>$5,000</td>
<td>$5,000</td>
<td>$5,000</td>
<td>$500</td>
<td>(DSIRE 2018)</td>
</tr>
<tr>
<td>Tax credit grade</td>
<td>F</td>
<td>C</td>
<td>F</td>
<td>F</td>
<td>C</td>
<td>(DSIRE 2018, Wavesolar 2018)</td>
</tr>
<tr>
<td>Investment tax credit (Federal)</td>
<td>30%</td>
<td>30%</td>
<td>30%</td>
<td>30%</td>
<td>30%</td>
<td>(DSIRE 2018)</td>
</tr>
<tr>
<td>Property tax exemption grade</td>
<td>A</td>
<td>A</td>
<td>A</td>
<td>A</td>
<td>A</td>
<td>(DSIRE 2018, Wavesolar 2018)</td>
</tr>
</tbody>
</table>
Performance payment grade

<table>
<thead>
<tr>
<th></th>
<th>D</th>
<th>D</th>
<th>D</th>
<th>A</th>
<th>F</th>
<th>(DSIRE 2018, Wavesolar 2018)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production based incentive ($/kWh)</td>
<td>0.0612 (for 10 years)</td>
<td>0</td>
<td>0</td>
<td>0.248 (for 10 years)</td>
<td>0</td>
<td>(DSIRE 2018)</td>
</tr>
<tr>
<td>Capacity based incentive</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>583 $/kW ac + 0.2519 $/kWh ac</td>
<td>(DSIRE 2018)</td>
</tr>
</tbody>
</table>

Financial incentives include tax credits, loan programs, Modified Accelerated Cost Recovery System (MACRS), investment and production-based incentives (IBI & PBI), and renewable energy credit programs. Tax credits are the dollar amount in tax savings that can reduce a considerable portion of the installation cost. MACRS is a five-year accelerated cost recovery system that includes a 50% first-year depreciation for renewable energy technologies. Investment and performance-based incentives are the payments that can be received at the federal or state level for the investment in or production of the solar systems respectively. Solar credits can be sold to utility companies looking to avoid penalties for not generating enough renewable energy as mandated for each state, which are determined based on Renewable Portfolio Standards (RPS). Alternatively, regulatory policies contain RPS, net metering, interconnection, Feed-in Tariff (FiT), electricity prices and solar permits (DSIRE 2018). RPS is a law enacted by an individual state to mandate that a specific percentage of all energy generation must be attained through renewable sources by a certain date. Net metering generally enables the customers to use the electricity generated by their systems and sends the excess energy back to the grid in exchange of credits in their current or next billing cycles. Interconnection is a set of policies related to connecting the solar system to the grid. Interconnection and net metering can be considered as a way of accounting for the changing relationship over the day between PV array output and local loads. This accounts
for sending any surplus day-shift electricity to the grid, while at night, power flow is from the grid. FiT is the receivable payment for the solar energy generated in non-net metering states. The electricity price from utility companies and resulting energy costs can affect in savings through generating electricity onsite. Because regional incentives and policies could differ among different cities and utility companies, we tried to compare the general conditions of the states (DSIRE 2018). However, in two of the selected states, Indiana and Texas, the existing conditions present larger differences, considering different locations, cities, and utility companies. Indiana has a cap of 1-MW for a solar PV system to be eligible for net metering; however, industrial facilities could be exempt from that cap. Texas provides more flexibility in terms of negotiating the conditions of incentives and regulatory policies in different areas of the state. For instance, a solar rebate program is available in San Antonio area, and net metering can be negotiated in different regions of the state (DSIRE 2018). Due to the mentioned uncertainties and the importance of net metering as a regulatory policy, availability and absence of net metering in Indiana and Texas are reported in the results section. To check the model reliability, sensitivity analyses are performed for several independent input variables which indicated the model robustness for changes in the assumed variables—see sensitivity analysis section. The model is fully documented for further evaluation and reproduction based on the guidelines for reporting simulation-based studies (Rahmandad and Sterman 2012).
<table>
<thead>
<tr>
<th>Main cost parameter assumption</th>
<th>States</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>PV module cost</td>
<td>All states</td>
<td>0.47 $/Wdc</td>
<td>(Fu, Feldman et al. 2018, PVinsights 2018)</td>
</tr>
<tr>
<td>Inverter</td>
<td>All states</td>
<td>4,500 $/unit</td>
<td>(ABB 2014)</td>
</tr>
<tr>
<td>BOS equipment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CA</td>
<td></td>
<td>0.24 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>FL</td>
<td></td>
<td>0.36 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>IN</td>
<td></td>
<td>0.26 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>NJ</td>
<td></td>
<td>0.30 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>TX</td>
<td></td>
<td>0.27 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>Installation Labor</td>
<td>CA</td>
<td>0.16 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>FL</td>
<td></td>
<td>0.11 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>IN</td>
<td></td>
<td>0.16 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>NJ</td>
<td></td>
<td>0.17 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>TX</td>
<td></td>
<td>0.11 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>Installer overhead</td>
<td>CA</td>
<td>0.18 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>FL</td>
<td></td>
<td>0.15 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>IN</td>
<td></td>
<td>0.16 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>NJ</td>
<td></td>
<td>0.17 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>TX</td>
<td></td>
<td>0.14 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>Permitting</td>
<td>All states</td>
<td>0.10 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>Fixed O&amp;M</td>
<td>All states</td>
<td>17 ± 10 $/kW/yr</td>
<td>(Walker 2017)</td>
</tr>
<tr>
<td>Engineering overhead</td>
<td>CA</td>
<td>0.35 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>FL</td>
<td></td>
<td>0.35 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>IN</td>
<td></td>
<td>0.36 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>NJ</td>
<td></td>
<td>0.37 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>TX</td>
<td></td>
<td>0.33 $/Wdc</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>Electricity cost</td>
<td>CA</td>
<td>TOU (0.08-0.15 $/kWh)</td>
<td>(URDB 2018)</td>
</tr>
<tr>
<td>FL</td>
<td></td>
<td>0.04 $/kWh</td>
<td>(URDB 2018)</td>
</tr>
<tr>
<td>IN</td>
<td></td>
<td>0.06 $/kWh</td>
<td>(URDB 2018)</td>
</tr>
<tr>
<td>NJ</td>
<td></td>
<td>0.03 $/kWh</td>
<td>(URDB 2018)</td>
</tr>
<tr>
<td>TX</td>
<td></td>
<td>0.07 $/kWh</td>
<td>(URDB 2018)</td>
</tr>
<tr>
<td>Federal income tax rate</td>
<td>All states</td>
<td>21%</td>
<td>(Pomerleau 2018)</td>
</tr>
<tr>
<td>State income tax rate</td>
<td>CA</td>
<td>8.84%</td>
<td>(Jared 2018)</td>
</tr>
<tr>
<td>FL</td>
<td></td>
<td>5.50%</td>
<td>(Jared 2018)</td>
</tr>
<tr>
<td>IN</td>
<td></td>
<td>6.00%</td>
<td>(Jared 2018)</td>
</tr>
<tr>
<td>NJ</td>
<td></td>
<td>9.00%</td>
<td>(Jared 2018)</td>
</tr>
<tr>
<td>TX</td>
<td></td>
<td>0.00%</td>
<td>(Jared 2018)</td>
</tr>
<tr>
<td>Sales tax</td>
<td>CA</td>
<td>8.54%</td>
<td>(Jared 2018)</td>
</tr>
<tr>
<td>FL</td>
<td></td>
<td>6.00%</td>
<td>(Jared 2018)</td>
</tr>
<tr>
<td>IN</td>
<td></td>
<td>7.00%</td>
<td>(Jared 2018)</td>
</tr>
<tr>
<td>NJ</td>
<td></td>
<td>6.87%</td>
<td>(Jared 2018)</td>
</tr>
<tr>
<td>TX</td>
<td></td>
<td>8.17%</td>
<td>(Jared 2018)</td>
</tr>
<tr>
<td>Property tax rate</td>
<td>CA</td>
<td>0.74% /yr</td>
<td>(Kiernan 2018)</td>
</tr>
<tr>
<td>FL</td>
<td></td>
<td>1.00% / yr</td>
<td>(Kiernan 2018)</td>
</tr>
</tbody>
</table>
## 2-3. Results

Electricity demand intensity range per annum for 20 3-digit NAICS industrial sectors along with the roof-mounted solar PV (on the roof of the establishments) energy generation in 50 U.S. states as a supply range are illustrated in Figure 2-3. The supply range per unit area is determined for high efficiency roof-mounted solar PV by using SAM (NREL 2016). According to the geographical location of each state, the lowest and highest supply range can meet 100% of the required energy for 19% and 57% of industrial sectors via high efficiency roof-mounted solar PVs respectively. Figure 2-3 can be categorized into three subgroups regarding the electricity demand intensity of the manufacturing sectors in comparison with the supply range. Sectors such as furniture and related products, textile product mills, apparel, and leather and allied products can be confident of utilizing roof-mounted solar PVs to meet 100% of their demands regardless of the manufacturing facility location. The second group includes miscellaneous, machinery, printing and related support, fabricated metal products, transportation equipment, beverage and tobacco products, wood products, and electrical equipment and computers sectors which should consider
geographical location to be able to generate 100% of their required energy through roof-mounted solar PVs. Finally, the third group contains textile mills, plastic and rubber products, computer and electronic products, food, nonmetallic mineral products, paper, chemicals, and primary metal as high energy intensive sectors that cannot rely on roof-mounted PVs solely for generating 100% of their required energy.

Figure 2-3: Electricity demand intensity for 20 3-digit NAICS industrial subsectors according to MECS database. Supply range shows the potentials of 50 U.S. states in generating energy through high efficiency roof-mounted solar PVs per unit area.

Figure 2-4a indicates average demand per month for 20 3-digit industrial sectors along with the potentials of energy generation per month through roof-mounted solar PVs in all U.S. states. Figure 2-4a shows that during summer time, 48% of the industrial sectors could count on roof-mounted solar PVs to meet 100% of their demands in all 50 states. These sectors include: textile product mills (314), apparel (315), leather and allied products (316), wood products (321), printing and related support (323), fabricated metal products (332), machinery (333), transportation equipment (336), furniture and related products (337), and miscellaneous (339). States potentials
for energy generation per month (the shaded area in Figure 2-4a) from roof-mounted PVs are presented in Figure 2-4b and 2-5 for each state separately. Not surprisingly, the lowest supply range from September to February belongs to Alaska as shown in Figure 2-4b. If Alaska is excluded, textile product mills (314), apparel (315), and furniture and related products (337) sectors can rely on roof-mounted solar PVs in any location for entire year. Arizona, Nevada and New Mexico with the highest solar insolation can meet the required demand from 52% to 76% of the sectors in spring and summer time. New Hampshire, Oregon, and Pennsylvania are among the lowest solar insolation states which can generate the required energy for 19% of the sectors entire year.

Figure 2-5 illustrates the monthly solar renewable energy generation potential per unit area in each state and the highest and lowest electricity demand intensity (kWh/m²/month) for the industrial sector (EIA 2014). Primary metal (sector 331) and furniture and related products (sector
are the highest and lowest electricity demand intensive sectors respectively when petroleum and coal products, sector 324, is excluded (Census-Bureau 2017).
Figure 2-5: Solar renewable electricity generation by state. Electricity generation potentials of each state per unit area per month are compared with the highest and lowest electricity demand intensity (primary metal and furniture and related products (kWh/m²/month)) of the industrial sectors excluding petroleum and coal products sector.

Figure 2-6 reports a comparison of solar PV average energy generation potentials in census regions and divisions of the United States and 20 industrial sectors average monthly demand. As shown in Figure 2-6, Hawaii provides the highest solar energy for four months from November to February. West Mountain region outperforms other divisions for the eight remaining months. In July and August, West Pacific region is in the second place while in June West North Central can generate more energy.
Figure 2-6: Average monthly energy demand for 20 3-digit NAICS industrial sectors and potential of roof-mounted solar PV monthly energy generation in census regions and divisions of the United States. West Mountain is the highest region in solar renewable energy generation from March to October while Hawaii outperforms other regions from November to February. West Pacific region comes next for July and August, while West North Central region can generate more solar energy in June. West South Central region is in the third place after Hawaii and West Mountain for October and November. Not surprisingly the highest variance belongs to Alaska from winter to summer. Northeast New England, Northeast Mid Atlantic, and East North Central regions are among the lowest solar insolation regions which can compete with South Atlantic and East South Central regions only in the summer. Only West Mountain region can meet the demand requirement for food (311), textile mills (313), plastics and rubber products (326), and computer and electronic products (334) sectors from May to August while West Pacific region can encounter the demand of textile mills just in July.

2.3.1. Case study economic analyses

The cost benefit analysis of developing roof-mounted PVs for a manufacturing facility is performed under both existing and the most progressive federal and state financial incentives and policies for PVs for manufacturing sector in the five selected states. NPV, LCOE and economic payback period are used as economic metrics in this study. To determine each economic metric, all of the cost factors for the industrial sector presented in the model development and parameters section including purchasing PV panels, installation, BOS, Operation and Maintenance (O&M), regional electricity costs, and regional financial incentives and policies are integrated into SAM. Despite the uncertainties associated with raw material prices, operating and investment costs over the next decades, the economic analysis still provides meaningful insights to manufacturers and decision makers on the feasibility of PV systems to power a manufacturing facility (Schulze,
Heidenreich et al. 2018). The economic factors are directly determined by SAM except the price of CO$_2$ equivalent abatement, which is calculated based on the NPV of each investment in the states of interest. A negative or positive price of CO$_2$ equivalent abatement indicates losses or profits, respectively, from the investment in a solar PV system.

**Economic Payback Time**

The economic payback time for renewable energy investments is compared for the five selected states for two scenarios. In the first scenario, the existing incentives and policies at the federal and state levels for solar renewable investments are considered. In the second scenario, progressive incentives imposed by the state of New Jersey, as the highest rank state in the U.S. (Wavesolar 2018), are considered for the selected states. Figure 2-7 compares economic payback time for both scenarios. As expected, when the existing conditions of each state are used, New Jersey outperforms all other states with 3 years economic payback period due to its most encouraging incentives (solar credit/rebate program). The rebate program in New Jersey provided under a solar loan program is a PBI at the rate of $0.248 per kWh for 10 years. The second best economic payback period is 3.7 years in California. Texas is third with an economic payback time of 4.9 years. If the solar rebate program of San Antonio (0.80 $/W with the maximum of $80,000 per commercial customer) is imposed, the economic payback period in Texas drops to 4.6 years. Since, net metering is negotiable in some of the cities in Texas; and, there is a 1-MW cap for systems can be qualified for net metering in Indiana, while the industrial sector systems might be eligible for net metering, availability and absence of this important policy is explored in this section. If net metering is not available in Texas and Indiana state-wide, then the investment would
not payback in 25 years. Florida has the longest economic payback period among the five states with 14.8 years. Despite the high sun irradiance, the “Sunshine State” shows the longest economic payback time because of the absence of effective incentives and policies. However, when New Jersey conditions are imposed in all states, New Jersey itself takes the longest payback period of 3 years because it has the lowest average solar insolation. Under the New Jersey incentives and regulatory conditions, California would have the shortest payback time of 1.9 years, followed by Texas with 2 years, Florida with 2.6 years, and Indiana with 2.7 years. Figure 2-7 and Table 2-4 illustrate these results.

![Figure 2-7: Economic payback time under two scenarios. In the first scenario (darker bars), each state operates with their existing financial incentives and regulatory policies as is. In the second scenario (lighter bars), the progressive financial incentives of the state of New Jersey are imposed.](image)

Furthermore, all five states are analyzed under the following conditions: 1) no financial incentives and policies; 2) availability of only financial incentives; 3) availability of only regulatory policies; and 4) availability of both incentives and policies. With no incentives or regulatory policies, none of the states can payback the investment over the 25-year period. When only financial incentives are available, just New Jersey can pay back the investment in 3.5 years.
Finally, when only regulatory policies are available, all the states except New Jersey can pay back the investment (9 years for CA, 14.3 for TX, 17.1 for IN, and 22.2 for FL), which shows the importance of generous PBI available in New Jersey.

*Levelized Cost of Energy (LCOE)*

LCOE is used by SAM, the NREL’s simulation tool, as an indicator of each state’s financial incentives. The states with better financial incentives—not regulatory policies—would have a lower LCOE. The LCOE is calculated using Equation (2-1)

\[
LCOE = -\frac{C_0 - \sum_{n=1}^{N} C_n}{\left(1 + d_{\text{nominal}}\right)^n} \left(1 + d_{\text{real}}\right)^{-n} \tag{2-1}
\]

Where,
- \(Q_n\) : Electricity generated by the system in year \(n\) (kWh).
- \(N\) : Analysis period in years
- \(C_0\) : Project equity investment amount
- \(C_n\) : Annual project cost in year \(n\)
- \(d_{\text{real}}\) : Real discount rate without inflation
- \(d_{\text{nominal}}\) : Nominal discount rate with inflation

\(C_n\) is the product of the LCOE and the quantity of electricity generated by the system in that year

\[
C_n = Q_n \times LCOE \tag{2-2}
\]

Project costs \(C_n\) include installation, O&M, financial costs and fees, and tax benefit or liability, and also account for incentives and salvage value. The annual cost \(C_n\) is nominal dollar and includes the effect of inflation as well (NREL 2016). Table 2-4 details the results for the LCOE and economic payback period for the five states under different conditions: 1) existing conditions;
2) absence of incentives and policies; and 3) incentives and policies based on the state of NJ. According to the LCOE formula used by SAM (NREL 2016), LCOE doesn’t alter when no cash incentives, which can reduce the project equity investment, is available (this can be considered as financial incentives while regulatory policies doesn’t affect the equity investment). On the other hand, incentives or policies that can reduce the entire expenditures would affect economic payback. Therefore, the LCOE results for existing conditions and availability of only financial incentives are equivalent; while, the results for availability of only regulatory policies and absence of incentives and policies are similar. Indiana has the highest LCOE under its existing condition followed by Florida and Texas at 5.23 cents/kWh, 5.14 cents/kWh, and 3.23 cents/kWh respectively. New Jersey could achieve the lowest LCOE under its existing conditions at -4.14 cents/kWh. By applying New Jersey conditions to other states, LCOE in those states would also drop significantly as shown in Table 2-4. These results indicate that the LCOE is very sensitive to the generous incentive of $0.248/kWh under New Jersey conditions. The negative figures illustrate that the value after tax cash flows is significantly higher than the initial investment in each state.

<table>
<thead>
<tr>
<th>State</th>
<th>Existing Conditions</th>
<th>No Incentives or Policies</th>
<th>NJ Conditions</th>
<th>Average Electricity Escalation Rate (%/yr)</th>
<th>LCOE (cents/kWh)</th>
<th>Economic Payback Period (Years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>California</td>
<td>1.07</td>
<td>6.49</td>
<td>-5.97</td>
<td>2.2</td>
<td>1.07</td>
<td>3.7</td>
</tr>
<tr>
<td>Florida</td>
<td>5.14</td>
<td>8.29</td>
<td>-5.03</td>
<td>2.5</td>
<td>5.14</td>
<td>14.8</td>
</tr>
<tr>
<td>Indiana</td>
<td>5.23</td>
<td>8.69</td>
<td>-4.57</td>
<td>2.1</td>
<td>5.23</td>
<td>10.8</td>
</tr>
<tr>
<td>New Jersey</td>
<td>-4.14</td>
<td>12.09</td>
<td>-4.14</td>
<td>1.4</td>
<td>-4.14</td>
<td>3.0</td>
</tr>
<tr>
<td>Texas</td>
<td>3.23</td>
<td>8.34</td>
<td>-6.21</td>
<td>1.1</td>
<td>3.23</td>
<td>4.9</td>
</tr>
</tbody>
</table>

**Table 2-4: LCOE and Economic Payback Period under a variety of financial conditions for each state**

*Price per Unit Mass of CO₂ Equivalent Abatement*
All states show a positive price of CO₂ equivalent abatement, as shown in Table 2-5 (existing conditions). Losses or profits can be determined by negative or positive price of CO₂ equivalent abated, respectively. As expected, the states with better financial incentives that result in higher NPV (CA and NJ) perform better than the others. It is interesting to note that while New Jersey appears to have the highest incentives and policies among all the states (DSIRE 2018), California still outperforms New Jersey at $151 to $93 per metric ton of CO₂ equivalent abatement price, due to higher NPV of the establishing solar PV systems for manufacturing facilities in CA. This favorable price results from better weather conditions for solar energy generation and higher savings in electricity bills in CA. The two most dominant factors on price of CO₂ equivalent abatement are: 1) available financial incentives/regulatory policies and 2) solar PV system electricity generation. Florida has the lowest dollar amount of lower than $1 per ton of CO₂ equivalent abatement followed by Indiana at $14. For instance, if net metering is not available in the selected states, the price would drop to lower than zero for all the states except New Jersey. Detail information for the price of CO₂ equivalent abatement are presented in Table 2-5. These variations in the price of CO₂ equivalent abatement confirms the results reported by McKinsey (Nauclér and Enkvist 2009).

<table>
<thead>
<tr>
<th>State</th>
<th>Abatement cost of CO₂ eq. ($/M t of CO₂ eq.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>New Jersey</td>
<td></td>
</tr>
<tr>
<td>California</td>
<td></td>
</tr>
<tr>
<td>Florida</td>
<td></td>
</tr>
<tr>
<td>Indiana</td>
<td></td>
</tr>
<tr>
<td>State</td>
<td>Existing Conditions</td>
</tr>
<tr>
<td>----------</td>
<td>---------------------</td>
</tr>
<tr>
<td>California</td>
<td>151.30</td>
</tr>
<tr>
<td>Florida</td>
<td>0.53</td>
</tr>
<tr>
<td>Indiana</td>
<td>14.21</td>
</tr>
<tr>
<td>New Jersey</td>
<td>92.99</td>
</tr>
<tr>
<td>Texas</td>
<td>41.88</td>
</tr>
</tbody>
</table>

2-3.2. Case study environmental analyses

For EPBT estimation, the CED of monocrystalline PV is used. The insights gathered from the literature (Kato, Murata et al. 1997, Alsema and de Wild 2005, Alsema, de Wild-Scholten et al. 2006, Fthenakis and Alsema 2006, Mason, Fthenakis et al. 2006, Jungbluth, Tuchschild et al. 2008, de Wild-Scholten 2009, Sherwani, Usmani et al. 2010, Peng, Lu et al. 2013, Yue, You et al. 2014, Collins, Powell et al. 2015, Murphy and McDonnell 2017, Armendariz-Lopez, Arena-Granados et al. 2018, Todde, Murgia et al. 2018, Zhou and Carbajales-Dale 2018) and a meta-analysis (Koppelaar 2017) are used for life cycle CED assumptions including the required energy for PV module materials, manufacturing, transportation, installation, BOS, O&M, and End-of-Life (EOL) processing.. The harmonized data considering 30% electricity conversion factor to primary energy equivalent for mono-crystalline silicon with a range between 240 and 1600 and the average of 645 kWh/m² is considered for CED assumptions (Zhou and Carbajales-Dale 2018). Furthermore, the avoided GHG and other air emissions (NOₓ, SO₂) via onsite electricity generation are calculated for each eGRID sub-region (EPA 2016). GHG and other air emissions avoided (NOₓ and SO₂) are calculated based on the amount of avoided electricity consumption in each eGRID sub-region for selected states with current marginal emission factors ranging 134-762 (kg/MWh) for CO₂ equivalent, 0.12-0.52 (kg/MWh) for NOₓ, and 0.14-0.52 (kg/MWh) for SO₂ by assuming no change in grid electricity emission factors over the 25 year period (EPA 2016).
**Energy Payback Time (EPBT)**

CED is used to calculate EPBT using Equation (2-3) defined by Fthenakis (2011):

\[
EPBT = \frac{(E_{mat} + E_{man} + E_{trans} + E_{ins} + E_{eol})}{E_{agen}} \left(\frac{1}{\eta_G}\right) - E_{aop}
\]

where,

- \(E_{mat}\): Primary energy demand to produce materials for PV system
- \(E_{man}\): Primary energy demand to manufacture PV system
- \(E_{trans}\): Primary energy demand to transport materials used during the life cycle
- \(E_{ins}\): Primary energy demand to install the PV system
- \(E_{eol}\): Primary energy demand for end of life management
- \(E_{agen}\): Annual electricity generation
- \(E_{aop}\): Annual energy demand for operation and maintenance in primary energy terms
- \(\eta_G\): Grid efficiency, primary energy to electricity conversion at the demand side

CED is compared to the net AC electricity generated by solar PV systems to determine EPBT. EPBT is related to the geographical location, sun irradiance, and cell efficiency. Table 2-6 shows a range of EPBT for the five states of interest based on different CED values reported in (Zhou and Carbajales-Dale 2018). EPBT for states with higher sun irradiance (CA and TX) is in the range of 1.2 to 1.4 years, while for the northern states (IN and NJ) it is approximately 30% longer in the range of 1.6 to 1.7 years. California’s EPBT is the shortest because of its highest annual energy generation through solar PV systems, followed by Texas, Florida, Indiana, and New Jersey. These results are consistent with what is reported by other researchers who considered SunPower module products for a utility size plant with a generation capacity of 579 MW (Francke, Armand et al. 2015).
Table 2-6: CED and EPBT information for the states of interest

<table>
<thead>
<tr>
<th>CED (kWh/m²)</th>
<th>EPBT (year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>Average</td>
</tr>
<tr>
<td>240</td>
<td>645</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

*Cumulative Air Emission Benefits*

Cumulative emission avoided during the 25-year duration of the study is calculated based on the amount of energy generated by the solar PV system including degradation and the emission of eGRID sub-regions in which the selected states are located. The emissions considered in this section include NO\textsubscript{x} and SO\textsubscript{2}. Figure 2-8 presents the cumulative avoided amount of each emission by using 1.75-MW solar PV systems to power manufacturing facilities in each state. Among the five states, Indiana shows the largest gain in the amount of avoided NO\textsubscript{x} at 32.72 metric ton, followed by California at 24.58 metric ton. Texas benefits the most by avoidance of 42.10 metric tons of SO\textsubscript{2} followed by Indiana at 41.52 metric tons. Battery manufacturers in Florida could reduce NO\textsubscript{x} and SO\textsubscript{2} emissions by 20.28 and 13.79 metric ton, respectively, while New Jersey could reduce these emissions by 18.82 and 19.19 metric ton, respectively. In contrast, a manufacturer in California could avoid SO\textsubscript{2} emission by only 2.25 metric ton.
Figure 2-8: Cumulative avoided air emissions in five states if using 1.75-MW roof-mounted solar PV systems to power manufacturing facilities. Indiana and Texas show largest gains in emission reductions from using solar energy. In California and Florida, the highest avoided emission is NOx while it is SO2 in the other states.

2-4. Sensitivity analysis

The model allows the user to allocate several values for the decision variables such as module cost, labor cost, electricity escalation rates and find the final values for the economic payback time, LCOE and NPV. The existing conditions of each state are used for the sensitivity analysis for two scenarios: in scenario 1, 50% of the assumed discount rate (5%), the minimum value of module price, labor cost, O&M from 2010 to 2018 according to NREL’s Q1 2018 report on U.S. solar photovoltaic system cost (Fu, Feldman et al. 2018), and the minimum electricity price escalation rates according to annual retail price of electricity increase for industrial sector from 2001 to 2017 in the selected states (EIA 2018) are considered separately; in scenario 2, 150% of the assumed discount rate, the maximum value of module price, labor cost, O&M (Fu, Feldman et al. 2018), and the electricity price escalation rates (EIA 2018) are assessed separately. Detail information on different values of decision variables are reported in Table 2-7.
Table 2-7: Decision variables changes for sensitivity analysis

<table>
<thead>
<tr>
<th>Decision variables for sensitivity analysis</th>
<th>States</th>
<th>Change (%/ yr)</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>PV module cost</td>
<td>All states</td>
<td>± 10.25</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>Labor cost</td>
<td>All states</td>
<td>± 6.25</td>
<td>(Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>Fixed O&amp;M</td>
<td>All states</td>
<td>± 52.63</td>
<td>(NREL 2016, Fu, Feldman et al. 2018)</td>
</tr>
<tr>
<td>Discount rate</td>
<td>All states</td>
<td>± 2.5</td>
<td>Assumed</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Electricity price escalation rates</th>
<th>Min change</th>
<th>Max change</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(% / yr)</td>
<td>(% / yr)</td>
<td></td>
</tr>
<tr>
<td>CA</td>
<td>0.025</td>
<td>2.231</td>
<td>(EIA 2018)</td>
</tr>
<tr>
<td>FL</td>
<td>0.057</td>
<td>4.701</td>
<td>(EIA 2018)</td>
</tr>
<tr>
<td>IN</td>
<td>0.272</td>
<td>4.909</td>
<td>(EIA 2018)</td>
</tr>
<tr>
<td>NJ</td>
<td>0.431</td>
<td>2.973</td>
<td>(EIA 2018)</td>
</tr>
<tr>
<td>TX</td>
<td>6.810</td>
<td>3.929</td>
<td>(EIA 2018)</td>
</tr>
</tbody>
</table>

Figures 2-9 to 2-13 illustrate the effects of the changes in module price, labor cost, O&M, electricity price escalation rate, and discount rate as independent variables on the economic payback time, LCOE, and NPV as response variables respectively in the states of interest. The black solid lines in the middle of Figures 2-9 to 2-13 indicate the values of the response variables used for the economic analysis in this study. The impact of the independent variables varies in different states. In California, New Jersey and Texas, O&M and module price have the highest impact on economic payback time while in Florida and Indiana electricity price escalation and O&M dominate the economic payback time the most. The discount rate has no effect on the economic payback time regardless of the states. Furthermore, the order of the dominant factors on LCOE is similar among the states of interest. LCOE is affected the most by changes in the discount rate followed by O&M with no effect for electricity price escalation rate. Finally, NPV is mostly dominated by discount rate, electricity price escalation rate, and O&M with different orders in the states of interest as presented in Figures 2-9 through 2-13.
Figure 2-9: California: Impacts of changes in module cost, labor price, O&M cost, electricity price escalation rate and discount value on economic payback time, LCOE and NPV in the state of California. The solid lines in the middle of the bars represent the value used in this study for the economic analysis.

Figure 2-10: Florida: Impacts of changes in module cost, labor price, O&M cost, electricity price escalation rate and discount value on economic payback time, LCOE and NPV in the state of Florida. The solid lines in the middle of the bars represent the value used in this study for the economic analysis.
Figure 2-11: Indiana: Impacts of changes in module cost, labor price, O&M cost, electricity price escalation rate and discount value on economic payback time, LCOE and NPV in the state of Indiana. The solid lines in the middle of the bars represent the value used in this study for the economic analysis.

Figure 2-12: New Jersey: Impacts of changes in module cost, labor price, O&M cost, electricity price escalation rate and discount value on economic payback time, LCOE and NPV in the state of New Jersey. The solid lines in the middle of the bars represent the value used in this study for the economic analysis.
Figure 2-13: Texas: Impacts of changes in module cost, labor price, O&M cost, electricity price escalation rate and discount value on economic payback time, LCOE and NPV in the state of Texas. The solid lines in the middle of the bars represent the value used in this study for the economic analysis.

Figure 2-14 indicates the impact of minimum and maximum values of module, labor and O&M cost, electricity price escalation rates, and discount rate altogether as independent variables on the electricity bill savings in 25-year period of the study as the response variable. Wider gaps represent higher impact on the annual savings in the electricity bills. According to Figure 2-14, California has the highest annual dollar saved in the electricity bills followed by Texas and Indiana. The widest gap represents the state of Indiana which has the saving range from under $300,000 to more than $980,000 in year 25\textsuperscript{th} of the study. New Jersey has the narrowest gap which represent the electricity bill savings of around $210,000 to slightly over $380,000 in year 25\textsuperscript{th}.

Figure 2-14: Annual savings in $ for electricity bills for the five selected states in 25 year study period. The saving ranges are determined based on the minimum and maximum values of the independent input variables (module $, labor $, O&M $, electricity price escalation rates, and discount rate) altogether.

Finally, after tax cash flow of each state under its existing conditions are provided in Figures 2-15.
2-5. Discussion and conclusion

Although this study focused on smaller facilities for roof-top generation, it is interesting to note that Tesla is already constructing the largest rooftop solar system to date to power its Gigafactory\textsuperscript{1} in Nevada (Lambert 2018). The vast investment and technology improvement in PV manufacturing that has many similarities with semiconductor manufacturing in terms of materials use, equipment, processes, and facilities. With the advent of new technologies such as aerosol jet printing to print and manufacture electronics, solar panel manufacturing is expected to significantly improve in the near future.

The objective of this chapter is to provide a systematic framework for the U.S. industrial sector, as the second largest energy consumer and the third largest GHG emitter, to reduce energy consumption and GHG emissions, and facilitate the transition to a low-carbon economy. The insights of the study are helpful for manufacturers to evaluate different U.S. states for consideration of solar PVs as a potential source of renewable energy for their facilities to set long-term targets. Our findings show that 70% of the industries could consider solar PVs for their required energy production during spring and summer time in the states such as Arizona, California, Colorado, Hawaii, Idaho, Minnesota, Nevada, New Mexico, Texas, and Wyoming. By considering efficiency improvement of manufacturing processes and solar PVs, higher proportion of the required energy for industrial facilities could be covered by using renewable solar energy. Despite the fact that each manufacturing facility is different, roof-mounted solar PV systems show
high potential in economic feasibility for locations that are not always obvious sunny locales. The analysis provides economic and environmental outcomes of different financial incentive and regulation scenarios for manufacturers in five states to distinguish among the renewable energy policies to enable viable onsite electricity generation.

Effective, strategic and strong long-term regulatory policies such as permits, net metering, interconnection, RPS, FiT and financial incentives like production-based incentives, and tax credit could directly or indirectly support the widespread adoption of PV systems for roof-top solar applications in manufacturing facilities. The results indicate that deployment of solar energy for the industrial sector not only can become environmentally advantageous but also economically attractive for the investors such as U.S. iron and steel sector (Karali, Park et al. 2017).

The case study shows that when there are no financial incentives or regulatory policies available, none of the states can payback the investment over the 25-year period of study. When states have only regulatory policies in effect (without financial incentives), net metering is the most significant policy (which was in effect in 73% of the cases explored by (Matisoff and Johnson 2017)), facilities in four out of five states (CA, FL, IN, TX) can achieve payback on the investment within 25 years. When considering only financial incentives, only facilities in New Jersey can achieve economic payback on the investment due to the higher cash incentives. When both financial incentives and regulatory policies are imposed at the same time, all the states can achieve payback on the investment within the 25-year period. The economic analysis indicates that the investment in New Jersey has the shortest economic payback period at 3 years because of its encouraging financial incentives and supportive policies. The results of this case study indicate
that net metering together with direct cash programs like production-based incentives play significant roles in the economic feasibility of the solar project and can be more effective than other incentives such as tax credits. Results are consistent with other research findings with regard to the effectiveness of incentives and policies provided to promote solar energy (Mormann 2012, Matisoff and Johnson 2017). Other economic factors were determined LCOE and NPV, and then used to calculate the price of CO₂ equivalent abatement per unit mass. The LCOE can be used as a metric to assess the profitability of the investment in renewable technologies. A comparison of the LCOE to the market price/regional cost of energy for the states of interest, reported in the section 2-2.2., illustrates that the LCOE for a solar PV system is lower than the regional cost of energy under the existing incentives and policies for the selected states except Florida.

From environmental impact analysis point of view, life cycle CED of solar PV panels is used to determine EPBT for each state. Surprisingly, all the states considered in this study, can provide EPBT of less than two years if the average value of CED for monocrystalline silicon is considered (Zhou and Carbajales-Dale 2018). Additionally, cumulative reduction of nitrogen oxide (NOₓ), sulfur dioxide (SO₂) are assessed for each state according to eGRID sub-region database (EPA 2016). The environmental analysis shows that Indiana could achieve the highest reduction of NOₓ. The highest gain of CO₂ equivalent abatement per metric ton belongs to California at $151 followed by New Jersey at $93, due to their progressive financial incentives. The current carbon credits range from $2 to $14 per ton and are provided under the common operating emissions systems Regional Greenhouse Gas Initiative (RGGI) that has nine-member states and the California system. These carbon credits are not sufficient to impact reduction in economic payback time or LCOE. If higher emission credits become available in the future, the
investment and energy generation through solar PV systems could increase in appeal to the manufacturing sector (Gibbs 2015, Zhang, Cho et al. 2018).

This study delivers a systematic step towards better understanding of solar PV energy generation potentials and its comparison with electricity demand intensity of industrial sectors across the United States. The industrial sector GHG emissions can be grouped into two categories: direct and indirect (EPA 2018). Direct emissions are the product of facility level activities which mostly related to onsite fossil fuel emissions for energy generation. Indirect emissions are produced offsite, however, associated with energy consumption at the facility level. Direct energy consumptions by manufacturers in the U.S. are accounted for machine drives (48%); process heating and boiler use (14%); facility heating, ventilation and air condition (9.5%); electrochemical processes (7%); process cooling and refrigeration (7.5%); lighting (6.5%); and miscellaneous processes (7.5%) (EIA 2014). By utilizing solar PVs onsite of the industrial facilities both direct and indirect energy consumptions and accordingly GHG emissions could be reduced.

Improving the impact of dollars spent is the objective of policy makers when providing policies and incentives for renewable energies which could be investigated in the future studies. The potential of developing a solar plant utilizing different types of solar modules (e.g., InGaP, InGa, CdTe and multi-crystalline) different efficiencies and consideration of energy storage systems could be investigated to determine enhancements to the environmental and economic tradeoffs. Storage systems have significant impacts on the economic and environmental feasibility of renewable energy technology investments; therefore, selecting a proper size storage system
plays a crucial role. Reports illustrated that the storage capacity has a significant impact on economic payback period and required to be carefully sized or just utilized a PV system without storage (Zhang, Cho et al. 2018). Another study discussed that the roof-mounted solar PVs with storage systems are not feasible in locations with low solar insolation although they could be suitable for other locations (Nicholls, Sharma et al. 2015). Finally, a few scenarios of electricity generation through renewable sources by considering an integrated intelligent storage and renewable energy generation systems which allow “auto-production” and “self-consumption” of electricity are evaluated (Germani, Landi et al. 2015). Therefore, selecting a proper size storage system requires precise investigation of location-based conditions.
Chapter 3 -
The Adoption of New Medical Technologies: The Case of Customized Individually Made Knee Implants

The aim of this chapter is to investigate the impact of insurance coverage, physicians’ preferences, manufacturing willingness toward new technology, and hospitals contracts on the adoption of customized individually made (CIM) knee implants, and to compare patient outcomes and cost-effectiveness of off-the-shelf (OTS) and CIM implants. A system dynamics simulation model is developed to study adoption dynamics of CIM and meet the research objectives. The model reproduced the historical data on primary and revision knee replacement implants obtained from the literature and the Nationwide Inpatient Sample. Then, the dynamics of adoption of CIM implants were simulated from 2018 to 2026. The rate of 90-day readmission, 3-year revision surgery, recovery period, time savings in operating rooms, and the associated cost within three years of primary knee replacement procedures were used as performance metrics. The simulation results indicate that, by 2026, an adoption rate of 90% for CIM implants can reduce the number of
readmissions and revision surgeries by 62% and 39%, respectively, and can save hospitals and surgeons 6% on procedure time, and cut down cumulative healthcare costs by approximately $38 billion. Our findings indicate that the CIM implants have the potential to deliver high-quality care while decreasing overall healthcare costs, but their adoption requires the expansion of current insurance coverage. This work presents a first systematic study to understand the dynamics of adoption of CIM knee implants and instrumentation. More broadly, the current modeling approach and systems thinking perspective could be utilized to consider the adoption of any emerging customized therapies for personalized medicine.
3-1. Introduction

The number of total knee replacements performed in the U.S. doubled from 2005 to 2015, with a disproportionate increase among younger adults (Weinstein, Rome et al. 2013, Ubel 2017). Currently, 6.7 million people are living with knee implants—about 20% more than the number of people living with heart failure (Ventola 2014, CDC 2016). The number of patients needing knee replacements is projected to grow to 3.5 million per year by 2030 (Maradit Kremers, Larson et al. 2015, American Academy of Orthopaedic Surgeons 2017). Approximately 60% of total hip and knee arthroplasties (THAs & TKAs) are covered by Medicare (Health 2014), and these procedures cost the U.S. federal government more than $7 billion for hospitalizations alone in 2014 (CMS 2018). The Centers for Medicare and Medicaid Services (Ramos, Wang et al. 2014) has targeted total joint replacement as a high-volume and high-cost procedure that should be subject to cost and quality control. Accordingly, bundled payment programs have been introduced in an attempt to reduce the costs of procedures and shorten length of stay for THAs and TKAs without sacrificing quality of care (Hart, Bergeron et al. 2015, Mears 2016). The emphasis on value in the bundled payment model demonstrates the importance of investigating the role of new technologies, such as additively manufactured customized individually made (CIM) knee implants and instrumentation, in increasing the efficiency and cost-effectiveness of knee procedures.

The Benefits and Drawbacks of Customized Individually Made (CIM) Knee Implants

Reports have indicated that patient satisfaction with off-the-shelf (OTS) implants can range from 75% to 92% (Chesworth, Mahomed et al. 2008, Bourne, Chesworth et al. 2010, Müller, Matziolis et al. 2012, Dunbar, Richardson et al. 2013, Tria 2013, Heekin and Fokin 2014, Choi
and Ra 2016). Customized implants have the potential to improve mechanical alignment (Carpenter, Holmberg et al. 2014, Dai, Scuderi et al. 2014), implant fit (Levengood and Dupee, Carpenter, Holmberg et al. 2014, Dai, Scuderi et al. 2014), bone coverage (overhang/underhung) and restoration (Levengood and Dupee), bone preservation (William B. Kurtz 2016), knee strength, range of motion, and axial rotation (Harman, Banks et al. 2012, Zeller, Sharma et al. 2016, Zeller, Kurtz et al. 2017). A 3D model, which is prepared by converting a series of 2D scanned images of the patient’s knee joint, is used to fabricate a CIM implant and instrumentation by using additive manufacturing/3D printing technologies. Better bone coverage could lead to less bleeding from exposed bone surfaces and less postoperative knee swelling, potentially resulting in an accelerated healing process and faster recovery (Culler, Martin et al., Chua and Chui 2016). The drawbacks of CIM implants include (typically) expensive than off-the-shelf implant, lack of long-term evidence for clinical outcomes, need for customized instrumentation, higher exposure to radiation in the process of axial imaging such as CT scanning, and increased complexity of the implant ordering system (Steinert, Beckmann et al. 2017).

**Major Obstacles to the Adoption of CIM Implants**

CIM implants have been slowly adopted in operating theaters since their introduction around 2011 (Gregg 2014). The widespread adoption of CIM implants faces many barriers. There is no long-term proven evidence that CIM implants can directly improve patient outcomes, whereas OTS implants have proven clinical outcomes. Surgeons have to maintain backup implants in case, during the procedure, they discover any errors such as contamination or damage in the CIM implants. Surgeons tend to prefer OTS implants because of their training, familiarity, and
comfort level with OTS. The new procedure involves potential increased malpractice liability insurance costs and legal risks due to ordering and administrative issues. CIM implants cost more than OTS implants, and third-party payers do not provide coverage for CIM procedures. Hospitals and surgeons are often locked into established contracts with OTS vendors. Furthermore, CIM implants, as an emerging technology, face natural resistance to adoption.

The higher upfront costs of CIM compared to OTS implants tend to discourage the adoption of CIM technology. Hospitals are typically paid a fixed amount as a “bundled payment” from both Medicare and third-party payers for all costs associated with TKA surgery and 90 days of care thereafter, including costs associated with implants, operating rooms, nursing, inpatient stay, post-discharge nursing, and physical therapy services. For such bundled payments, hospitals gain profit only if expenses are less than the fixed reimbursement. Since CIM TKA implants are likely to cost 20%-30% (Schrock 2014, Lewis 2015) more than OTS TKA implants due to the cost of preoperative imaging and expensive manufacturing processes, hospitals often resist adoption of CIM implants. Moreover, potential long-term savings that could accrue from the use of CIM implants (e.g., as a result of fewer revision surgeries) are not relevant in a 90-day bundled payment.

Understanding the reimbursement dynamics on the national level is challenging because of health plan complexities and high variability of costs in knee replacement procedures depending on geographical location, types of services provided, and other factors. In this study, we use a system dynamics simulation model to produce a comparative quality analysis and investigate the outcomes for CIM vs. OTS TKAs, considering the coverage of insurance bundled payment programs. While the average reimbursement rate for OTS procedures is estimated based on the
current bundled payment policies (Olmos 2010, Lewis 2016, Greengard 2017, Romualdez 2017), the coverage for CIM procedures is investigated at different levels.

The simulation model is developed to study the long-term effects of the dynamic evolution of knee replacement procedures, coverage, and possible health quality improvement under a variety of “what-if” scenarios. The simulation model forecasts the dynamics of CIM and OTS adoption and how CIM implants can emerge in an established market. Benefits of CIM implants on some categories of patient outcomes (Culler, Martin et al., Levengood and Dupee, Carpenter, Holmberg et al. 2014, Dai, Scuderi et al. 2014, Chua and Chui 2016, William B. Kurtz 2016, Zeller, Sharma et al. 2016, Zeller, Kurtz et al. 2017) are incorporated in the simulation model. Established contracts between hospitals/surgeons and OTS manufacturers and natural resistance to adoption of a new product/technology are considered barriers to CIM adoption in the model. Over time, these barriers change dynamically with the ratio of CIM adopters to OTS users and manufacturers’ production plans to fabricate CIM products (Rosenthal 2017). The model explores how different factors interact to potentially improve patient outcomes and produce savings that can be distributed among the stakeholders by using CIM implants. Specifically, the generalizable contributions of this work include:

- A novel framework with the focus on quantitative tradeoff assessment of patient satisfaction and wellbeing as well as the economic benefits of utilizing CIM implants.
- The analysis to support decision and policy makers by providing helpful insights for adoption of CIM implants to improve healthcare economics as well as the social wellness.
The demonstration of a comparative analysis of investigating the influence of different levels of insurance coverage for CIM implants as an exogenous factor and other barriers mentioned in this chapter as endogenous factors on the adoption of these products.

While the modeling approach focuses on the adoption dynamics of CIM implants, it is applicable to evaluate a broad range of emerging customized therapies in the era of personalized medicine.

The rest of the chapter is organized as follows: Section 3-2 presents the methods including model development, data, parameters, formulation, model validation, and verification. Section 3-3 provides the results and sensitivity analysis. Section 3-4 contains the discussion of the study. Section 3-5 reviews the study limitations. Section 3-6 includes the conclusion and potential future work.

3-2. Methods

3-2.1. The Model

System dynamics (SD) has been widely used to study complex problems in public health and health policy (Homer 1987, Homer and Hirsch 2006, Ghaffarzadegan, Ebrahimvandi et al. 2016, Homer, Milstein et al. 2016, Ansah, Koh et al. 2017, Jalali, Rahmandad et al. 2017, Paul and Venkateswaran 2017, Duintjer Tebbens and Thompson 2018, Rogers, Gallaher et al. 2018, Sterman 2018). Also, the classical approach to evaluating market adoption developed by Bass (Bass 1969) predicted S-shaped growth for adoption. Extensions of the Bass model have been shown to be useful for modeling innovation diffusion (Milling 1996, Milling 2002,
Ghaffarzadegan, Rad et al. 2018), and have been widely used to model diffusion in a broad range of products and issues (Bass 1980, Maier 1998, Paich, Peck et al. 2011, Ghaffarzadegan, Ebrahimvandi et al. 2016, Jalali, Ashouri et al. 2016, Keith, Sterman et al. 2016). Though the structure of our SD model is based on the Bass model, it includes additional factors related to coverage control, performance-related improvements, and information distribution. Furthermore, the evaluation stage in the adoption process and its interrelated dynamics have been incorporated.

The model simulates changes under a variety of what-if scenarios, e.g., alternative coverage policies for CIM implants, from 2018 to 2026, which can be expanded for trajectories beyond 2026. Figure 3-1 illustrates a high-level overview of the model, presenting the causal loop diagram (CLD) and patient flow. The two main factors that influence the adoption of CIM implants are out-of-pocket surgery costs for patients and surgeons’ pro-CIM recommendations. The feedback loops represent how these two factors change dynamically within the model. The upper half of the CLD links the coverage for CIM to total costs of healthcare through the adoption of CIM implants. The lower half, presents the impacts of manufacturers, sales force, and surgeons’ preference on the adoption of CIM implants. Hospitals often hesitate to select more expensive products due to their set fee bundled contracts with insurance companies for the episode of care, i.e., TKA procedures in this study. This creates the balancing feedback loop (Loop B, in CLD) for hospitals and insurance companies’ expenditures and coverage rates, which explains insurers’ short-term focus. In contrast, the revision surgery and readmission reinforcing loop (Loop R1) presents the long-term effects of coverage rate considering better patient outcomes in some categories through CIM adoption. Wider adoption of CIM would lead to improvement in some categories of patient outcomes, which in turn would result in quicker recovery, as well as
reductions in revision surgeries and readmissions (Culler, Martin et al., Schairer, Vail et al. 2014); these positive changes would eventually decrease the costs for all the stakeholders.

Figure 3-1: High-level version of causal loop diagram (CLD) and patient flow in the SD model. Positive (+) links between any variables in the CLD present changes in the same direction for those variables, while negative (–) links illustrate changes in the opposite direction. CIM adoption rates by patients are influenced by “out-of-pocket surgery costs for patients” and “surgeons’ recommendations for CIM.” Surgery costs for patients are dependent on levels of coverage for CIM, while surgeons’ recommendations are driven by surgeons’ preferences, which are mainly influenced by outcomes for previous patients, stipulations of established contracts with vendors and sales representative for hospitals and surgeons, and levels of coverage for CIM procedures. The balancing loop (B) and four reinforcing loops (R1, R2, R3, and R4) are the main feedback loops in the CLD. Expensive coverage acts as a balancing loop (B) that slows down CIM adoption rates, while the reinforcing loops try to promote CIM adoption by improving patient outcomes, shortening recovery, reducing the number of revision surgeries and readmissions, curtailing total healthcare costs, and expanding the CIM market share. Patient flow shows a simplified process for knee replacement surgery for both OTS and CIM implants. The upper part represents the knee replacement surgical procedure, and the lower part describes the patient flow during post-operative recovery. The discharge, readmission, and revision surgery rates vary between OTS and CIM procedures.

Higher coverage for CIM TKAs would encourage CIM adoption and increase the chances that surgeons would recommend CIM (loop R2). The next essential factor affecting surgeons’ recommendations is their preferences, as evidenced by the outcomes of previous procedures, which creates the third reinforcing feedback loop (R3). Evidence of better surgery performance
and outcomes would make surgeons more likely to recommend CIM implants and instrumentation; however, there will be time lag for surgeons to observe the better performance and use new products. Currently, surgeons’ preference for OTS is reinforced by their level of comfort, training, familiarity with OTS, and greater availability of information regarding OTS clinical outcomes.

Another factor that influences surgeons’ recommendations of CIM is vendor-established contracts with hospitals and surgeons, which encourages or discourages manufacturers to shift to CIM (Loop R4). Over the long run, manufacturers’ willingness to produce CIM is affected by market share for CIM. If manufacturers observed an increase in the market share of CIM implants driven by their better patient outcomes, OTS implant producers would become more interested in incorporating customized elements into their standard sizes—albeit with a significant time lag. Moreover, patients’ willingness to adopt CIM implants due to their social awareness is also considered a factor of influence in the simulation model.

The patient flow from early stages, when knee replacements are recommended, through post-operative recovery is shown in Figure 3-1. Surgery and post-surgery are two main sections in the patient flow. In the model, patients are initially separated into two groups depending on the surgery they undergo, OTS or CIM. This distribution changes over time, since it is dynamically driven by the factors discussed above and shown in the CLD. After surgery, patients are discharged home (with or without home visiting health services), skilled nursing facilities or rarely rehabilitation centers. Early research shows a statistically significant difference in the discharge destination distribution after hospitalization for CIM vs. OTS TKAs: CIM TKA patients are more likely to be discharged home, resulting in savings for insurers and patients (Culler, Martin et al.).
Recently, outpatient TKA, which still needs more clarification in the definition of length of stay (Bovonratwet, Webb et al. 2017, Nelson, Webb et al. 2017, Sher, Keswani et al. 2017, Vehmeijer, Husted et al. 2018), has gained momentum due to its potentials to minimize the costs among healthy patients; however, nationwide data demonstrate a higher risk of perioperative surgical and medical complications including component failure, infection, knee stiffness, and deep vein thrombosis (Arshi, Leong et al. 2017) discussed further in the limitation section. The driving factors of the discharge destination, for both inpatient/outpatient OTS and CIM implants procedures, are early patient performance, pain control, social support, conducive home environments, willingness to discharge to specific destination, and medical comorbidities (Lake 2017).

In our model, early patient performance, as a function of average range of motion, axial rotation of the knee, and implant lift-off in early and late flexion, is used as a measure of patient outcome after TKA procedures. After surgery, patients may be readmitted within 90 days or undergo revision surgeries within a three-year period. We considered these two periods due to their common use and data availability. Although patients may experience complications that force them to have unscheduled readmissions or revision surgeries, in the model, the severity of those complications varies between patients using OTS and CIM implants, based on implant functionality/patient outcome (Culler, Martin et al., Carpenter, Holmberg et al. 2014, William B. Kurtz 2016, Zeller, Sharma et al. 2016). The model is fully documented for further evaluation and reproduction in the next sections. The documentation follows a guideline for reporting simulation-based studies (Rahmandad and Sterman 2012).
3-2.2. Data and Model Parameters

We used aggregated historical data obtained from the literature (Kurtz 2005, Kurtz, Ong et al. 2007, Kurtz, Ong et al. 2011, Wengler, Nimptsch et al. 2014, Bozic, Kamath et al. 2015, Inacio, Paxton et al. 2017) and the National Inpatient Sample. The time series data, parameter values, and their references are presented in this section.

3-2.2.1. Time Series

The system dynamics model is designed to project the patient growth rate and the number of patients in 2018 from historical data—patients requiring knee replacement in the U.S. from 1990 to 2012. Furthermore, the estimated model is used to project the trend through 2026. Table 3-1, and Figures 3-2 and 3-3 present the summary of the number of patients who have had either primary or revision knee replacement surgeries. These datasets are used in the model to replicate the number of patients and estimate the future trends.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of patients undergone primary knee replacement</td>
<td>Figure 3-2</td>
<td>(Kurtz, Ong et al. 2011)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Kurtz 2005)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Inacio, Paxton et al. 2017)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Bozic, Kamath et al. 2015)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Wengler, Nimptsch et al. 2014)</td>
</tr>
<tr>
<td>Number of patients undergone revision knee replacement</td>
<td>Figure 3-3</td>
<td>(Kurtz, Ong et al. 2011)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Kurtz 2005)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Bozic, Kamath et al. 2015)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Wengler, Nimptsch et al. 2014)</td>
</tr>
</tbody>
</table>
2.2.2. Model Parameters

Tables 3-2 and 3-3 provide details on cost, patient outcome, and time related variables used in the model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Cost of Hospital Stay</td>
<td>~$4,000/day</td>
<td>(Fay 2017) and (Culler, Martin et al.)</td>
</tr>
</tbody>
</table>
Cost of Operation Room: ~$1500/hr (Haas and Kaplan 2017)
Cost of Surgeon: ~$1000/hr (Haas and Kaplan 2017)
OTS Knee Implant Cost*: ~$7,000/implant (Robinson, Pozen et al. 2012)
Cost of Office Visit for Readmitted Patients: ~$500/patient (Bluebook 2017)
Cost of Entire Revision Procedure: ~$40,000/patient (Bluebook 2017)
Insurance coverage for OTS: 0.9 (Romualdez 2017, Lewis 2016, Samuel Greengard 2017)
Cost of Hospitalization in Rehab or Nursing Facility for Custom: ~$8331/patient (Culler, Martin et al.)
Cost of Hospitalization in Rehab or Nursing Facility for OTS: ~$11134/patient (Culler, Martin et al.)
Cost of Rehabilitation at Home or with Health Care for Custom: ~$3776/patient (Culler, Martin et al.)
Cost of Rehabilitation at Home or with Health Care for OTS: ~$3815/patient (Culler, Martin et al.)

*The cost of OTS implants is according to 2012 price which has probably decreased by about 25%-30%. Since, in our model, the cost of CIM implants is calculated based on OTS price, therefore, that difference in magnitude would not have a significant impact on the results.

Model parameters are constant during the simulation. Table 3-3 presents a summary of the parameters, their values, and resources.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waiting Time for Surgery</td>
<td>120 Days</td>
<td>(OLIPHANT 2017)</td>
</tr>
<tr>
<td>Initial Number of Patients at first month of 1990</td>
<td>10750</td>
<td>(Kurtz 2005)</td>
</tr>
<tr>
<td>Initial Number of Patients Used Custom Implants (2016)</td>
<td>50000</td>
<td>Conformis Inc. (Inc. 2016)</td>
</tr>
<tr>
<td>Rate of Patients Discharge to Home after OTS Surgery</td>
<td>0.639</td>
<td>(Culler, Martin et al.)</td>
</tr>
<tr>
<td>Rate of Patients Discharge to Home after CIM Surgery</td>
<td>0.712</td>
<td>(O’Halloran 2016)</td>
</tr>
<tr>
<td>Time to decide on Home Discharges</td>
<td>2 days</td>
<td>(American Academy of Orthopaedic Surgeons 2017)</td>
</tr>
<tr>
<td>Time to Recover Completely after OTS Surgery</td>
<td>4 weeks</td>
<td>(Samuel Greengard 2017)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(BoneSmart 2017)</td>
</tr>
<tr>
<td>Parameters</td>
<td>Value</td>
<td>Source</td>
</tr>
<tr>
<td>----------------------------------------------------------------------------</td>
<td>----------------------------</td>
<td>----------------------------------------------------------</td>
</tr>
<tr>
<td>90 Days OTS Readmission Rate</td>
<td>29.2%</td>
<td>(Culler, Martin et al.)</td>
</tr>
<tr>
<td>90 Days CIM Readmission Rate</td>
<td>17%</td>
<td>(Schairer, Vail et al. 2014)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Ramos, Wang et al. 2014)</td>
</tr>
<tr>
<td>3 Year Revision Surgery Rate</td>
<td>5.5%</td>
<td>(AJRR 2018)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(NJR 2018)</td>
</tr>
<tr>
<td>Initial Orthopedic Surgeons Population</td>
<td>8734</td>
<td>AJRR (Registry 2017)</td>
</tr>
<tr>
<td>Net Orthopedic Surgeon Population Increase</td>
<td>2% Increase from 2000-2020</td>
<td>(Iorio, Robb et al. 2008)</td>
</tr>
<tr>
<td>Surgeon to Patient Contact Rate</td>
<td>29 /Month</td>
<td>(Rechtoris 2015)</td>
</tr>
<tr>
<td>Custom Average Hospital Stay</td>
<td>2.97 days</td>
<td>(Culler, Martin et al.)</td>
</tr>
<tr>
<td>OTS Average Hospital Stay</td>
<td>3.2 days</td>
<td>(Culler, Martin et al.)</td>
</tr>
<tr>
<td>OTS Range of Motion (ROM)</td>
<td>0.71</td>
<td>(Zeller, Sharma et al. 2016)</td>
</tr>
<tr>
<td>OTS Axial Rotation</td>
<td>0.22</td>
<td>(Zeller, Sharma et al. 2016)</td>
</tr>
<tr>
<td>OTS Condyle liftoff (early flexion)</td>
<td>0.357</td>
<td>(Zeller, Sharma et al. 2016)</td>
</tr>
<tr>
<td>OTS Condyle liftoff (late flexion)</td>
<td>0.143</td>
<td>(Zeller, Sharma et al. 2016)</td>
</tr>
<tr>
<td>Custom Range of Motion (ROM)</td>
<td>0.77</td>
<td>(Zeller, Sharma et al. 2016)</td>
</tr>
<tr>
<td>Custom Axial Rotation</td>
<td>0.315</td>
<td>(Zeller, Sharma et al. 2016)</td>
</tr>
<tr>
<td>Custom Condyle liftoff (early flexion)</td>
<td>0</td>
<td>(Zeller, Sharma et al. 2016)</td>
</tr>
<tr>
<td>Custom Condyle liftoff (late flexion)</td>
<td>0.25</td>
<td>(Zeller, Sharma et al. 2016)</td>
</tr>
<tr>
<td>Time of OTS Procedure</td>
<td>~2 hrs</td>
<td>Interview (Kurtz 2017)</td>
</tr>
<tr>
<td>Time reduction during the procedure for Custom</td>
<td>~0.25 hrs</td>
<td>Interview (Kurtz 2017)</td>
</tr>
</tbody>
</table>

The model reproduces the historical patterns along with the projected trends for data sources —more details on model formulation, calibration and validation are presented in the next section. The simulation model begins with a status quo base case scenario representing the current state of knee replacements in the U.S., and then uses the projected numbers, derived from data sources, for future trends.
3-2.3. Model Formulation, Calibration and Validation

In this section, the model formulation is presented in the similar format as Vensim software. The equations are listed in two sections as simulation set up and main equations.

Also, the Vensim file can be downloaded from: http://jalali.mit.edu/medical-tech-adoption

3-2.3.1. Simulation Set up

1. INITIAL TIME = 0 (Represents the beginning of 2018)  
   Unit: Month

2. FINAL TIME = 108 (Represents the end of 2026) 
   Unit: Month

3. SAVEPER = TIME STEP  
   Unit: Month

4. TIME STEP = 0.0625  
   Unit: Month

3-2.3.2. Main Equations

5. Total Revision Surgeries=  
   Rate of Custom Revision Surgeries in 3 Years + Rate of OTS Revision Surgeries in 3 Years  
   Unit: People/Month

6. Readmission ratio=  
   Total Readmission/Rate of Incoming Patients  
   Unit: Dmnl

7. Revision Surgery ratio=  
   Total Revision Surgeries/Rate of Incoming Patients  
   Unit: Dmnl

8. Total Readmission=  
   Rate of Custom Readmission in 90 days + Rate of OTS Readmission in 90 days  
   Unit: People/Month

9. Accumulative Number of Patients Undergone Rev Surgery=
Custom Patients Undergone Revision Surgery + OTS Patients Undergone Revision Surgery
   Unit: Patients

10. Custom Sales Reps Influence on Surgeons=
   SMOOTH3 (Min (Manufacturer Willingness to Produce Custom, Sales Reps Influence on Promoting OTS), Time for Custom Reps to Adjust)
   Unit: Dmnl
   Comment: Considering the initial value for OTS sales force influence and required time for them to change their interests based on the manufacturers’ willingness to produce custom implants. If manufacturers’ willingness passes the OTS sales force influence on promoting, then the OTS sales force promoting would change their interests to promote custom implants.

11. Accumulative Number of Patients Readmitted in 90 days after Primary Surgery=
   Custom Patients Readmitted + OTS Patients Readmitted
   Unit: Patients

12. Time savings for Surgeons per Month=
   Custom Patients*Time reduction during the procedure
   Unit: Hour/Month
   Comment: Time can be saved per month for surgeons and hospitals if using custom implants

13. Rate of Incoming Patients=
   Number of Patients Undergo the Surgery at 2017*(Patient Increase Rate + 1)^Time1
   Unit: People/Month
   Comment: Exponential growth for incoming patients

14. Custom total recovery cost rates=
   Custom Cost of Hospital Stay per Month + Custom Cost of Rehab Stay per Month +
   Custom Cost of Rehabilitation at Home per Month
   Unit: Dollar/Month
   Comment: Total cost of custom recovery per month

15. OTS total recovery cost rates=
   OTS Cost of Hospital Stay per Month + OTS Cost of Rehab Stay per Month + OTS Cost of Rehabilitation at Home per Month
   Unit: Dollar/Month
   Comment: Total cost of OTS recovery per month

16. Patients Deciding on Knee Replacement Method=
   INTEG (Rate of Incoming Patients-Patients Using Custom-Patients Using OTS, Initial Number of Patients at 2017)
Unit: Patients
Comment: Dividing incoming patients into two groups (OTS and Custom)

17. OTS Patients=
   Patients Using OTS
   Unit: People/Month

18. Custom Patients=
   Patients Using Custom
   Unit: People/Month

19. Adoption from recommendation=
   Surgeons Recommendation Effectiveness on Surgeons for Custom*Contact with adopters
   Unit: Surgeon/Month
   Comment: It is based on the recommendation effectiveness and contact with the adopters

20. Contact with adopters=
   Probability of Contacts with Adopters*Social contact
   Unit: Surgeon/Month

21. Surgeons Becoming Interested=
   IF THEN ELSE (Switch to Block Custom Surgery=1, Adoption from recommendation *
   Custom Sales Reps Influence on Surgeons, 0)
   Unit: Surgeon/Month
   Comment: To become interested, adoption from recommendation of other surgeons and
   influence of the sales reps are considered together.

22. Surgeon patient contact=
   Patients Deciding on Knee Replacement Method*Surgeon to Patient Contact Rate*Probability of Contacts with Adopters
   Unit: People/Month

23. Social contact=
   Surgeon to Adopters Contact Rate*Surgeons NOT Willing to Adopt
   Unit: Surgeon/Month

24. Custom Rate of Discharge to home after Rehab=
   Custom Discharged to Rehab or Skilled Nursing Facility/Custom Duration of staying at Rehab
   Unit: People/Month
   Comment: Custom patients going home after rehab recovery

25. OTS Cost of Hospital Stay per Month=
(OTS Home Recovery Complete + OTS Rate of Discharge to home after Rehab)*Cost of Hospitalization in Hospital for OTS
   Unit: Dollar/Month
   Comment: Cost per month for hospital stay for OTS implant patients

26. OTS Cost of Readmission per Month=
   Price of Office Visit for Readmitted Patients*Rate of OTS Readmission in 90 days
   Unit: Dollar/Month

27. OTS Cost of Rehab Stay per Month=
   Cost of Hospitalization in Rehab or Nursing Facility for OTS*OTS Rate of Discharge to home after Rehab
   Unit: Dollar/Month
   Comment: Cost per month for rehab stay for OTS implant patients

28. OTS Cost of Rehabilitation at Home per Month=
   Cost of Rehabilitation at Home or with Health Care for OTS* OTS Home Recovery Complete
   Unit: Dollar/Month
   Comment: Cost per month for home stay for OTS implant patients

29. OTS Cost of Revision Surgery per Month=
   Cost of Entire Revision Procedure*Rate of OTS Revision Surgeries in 3 Years
   Unit: Dollar/Month

30. Custom Total Cost of the Entire Process=
   Custom Accumulative $ of Readmission + Custom Accumulative $ of Revision + Total Recovery Cost of Custom + Custom Accumulative Cost of Procedures
   Unit: Dollar
   Comment: Total cost including cost of procedure, recovery, readmission, and revision surgery

31. OTS Discharged to Home or Home with Health Care =
    INTEG (OTS Rate of Discharge to home after Rehab + Rate of OTS Discharge to Home-OTS Home Recovery Complete, 0)
    Unit: Patients

32. OTS Discharged to Rehab or Skilled Nursing Facility =
    INTEG (Rate of OTS Discharge to Rehab-OTS Rate of Discharge to home after Rehab, 0)
    Unit: Patients

33. Custom Discharged to Home or Home with Health Care =
    INTEG (Custom Rate of Discharge to home after Rehab + Rate of Custom Discharge to Home-Custom Home Recovery Complete, 0)
**Unit:** Patients

34. Custom Discharged to Rehab or Skilled Nursing Facility =
   INTEG (Rate of Custom Discharge to Rehab-Custom Rate of Discharge to home after
   Rehab, 0)
   **Unit:** Patients

35. Custom Accumulative Cost of Rehab Stay=
   INTEG (Custom Rehab $, 0)
   **Unit:** Dollar

36. Custom Accumulative Number of Patients=
   INTEG (Custom Patients, 0)
   **Unit:** People

37. OTS Home $=
   OTS Cost of Rehabilitation at Home per Month
   **Unit:** Dollar/Month

38. Total Recovery Cost of OTS=
   OTS Accumulative Cost of Hospital Stay + OTS Accumulative Cost of Rehab Stay + OTS
   Accumulative Cost of Home Recovery
   **Unit:** Dollar
   **Comment:** Total accumulative recovery cost for OTS

39. OTS Hospital $=
   OTS Cost of Hospital Stay per Month
   **Unit:** Dollar/Month

40. Percentage of Home Discharge for Custom=
   100* XIDZ (Rate of Custom Discharge to Home, Rate of Custom Discharge to Rehab, 0)
   **Unit:** Dmnl

41. Custom Hospital $ =
   Custom Cost of Hospital Stay per Month
   **Unit:** Dollar/Month

42. OTS Accumulative $ of Readmission=
   INTEG (OTS Readmission, 0)
   **Unit:** Dollar

43. Custom Accumulative $ of Readmission=
   INTEG (Custom Readmission, 0)
   **Unit:** Dollar
44. Custom Accumulative $ of Revision=
   INTEG (Custom Revision, 0)
   **Unit:** Dollar

45. Custom Accumulative cost of Home Recovery=
   INTEG (Custom Home $, 0)
   **Unit:** Dollar

46. Custom Accumulative Cost of Hospital Stay=
   INTEG (Custom Hospital $, 0)
   **Unit:** Dollar

47. Custom Accumulative Cost of Procedures=
   Custom Cost of Surgery*(Custom Accumulative Number of Patients) + OTS Product Cost*Multiplication of OTS Product Cost for Price of Custom Implants*(Custom Accumulative Number of Patients)
   **Unit:** Dollar
   **Comment:** Total accumulative procedure cost for custom

48. Percentage of Rev Surgery Custom Patients=
   100* XIDZ (Custom Patients Undergone Revision Surgery, Custom Patients Recovering at Home, 0)
   **Unit:** Dmnl

49. OTS Accumulative Number of Patients=
   INTEG (OTS Patients, 0)
   **Unit:** People

50. Probability of Contact with Custom Patients Discharged to Home=
   XIDZ (Custom Patients Recovering at Home, OTS Patients Recovering at Home + Custom Patients Recovering at Home, 0)
   **Unit:** Dmnl

51. Custom Cost of Rehabilitation at Home per Month=
   Cost of Rehabilitation at Home or with Health Care for Custom*Custom Home Recovery Complete
   **Unit:** Dollar/Month
   **Comment:** Cost per month for home stay for custom implant patients

52. OTS Rate of Discharge to home after Rehab=
   OTS Discharged to Rehab or Skilled Nursing Facility/OTS Duration of staying at Rehab
   **Unit:** People/Month
   **Comment:** OTS patients going home after rehab recovery
53. OTS Readmission=
   OTS Cost of Readmission per Month
   **Unit:** Dollar/Month

54. OTS Rehab $=
   OTS Cost of Rehab Stay per Month
   **Unit:** Dollar/Month

55. Custom Cost of Hospital Stay per Month=
   (Custom Home Recovery Complete + Custom Rate of Discharge to home after Rehab)*Cost of Hospitalization in Hospital for Custom
   **Unit:** Dollar/Month
   **Comment:** Cost per month for hospital stay for custom implant patients

56. Custom Cost of Readmission per Month=
   Price of Office Visit for Readmitted Patients*Rate of Custom Readmission in 90 days
   **Unit:** Dollar/Month

57. Custom Cost of Rehab Stay per Month=
   Cost of Hospitalization in Rehab or Nursing Facility for Custom*Custom Rate of Discharge to home after Rehab
   **Unit:** Dollar/Month
   **Comment:** Cost per month for rehab stay for custom implant patients

58. Custom Cost of Revision Surgery per Month=
   Multiplication of OTS Rev Surgery Price*Cost of Entire Revision Procedure*Rate of Custom Revision Surgeries in 3 Years
   **Unit:** Dollar/Month

59. Percentage of Rev Surgery OTS Patients=
   100* XIDZ (OTS Patients Undergone Revision Surgery, OTS Patients Recovering at Home, 0)
   **Unit:** Dmnl

60. OTS Accumulative Cost of Rehab Stay=
   INTEG (OTS Rehab $, 0)
   **Unit:** Dollar

61. Custom Revision=
   Custom Cost of Revision Surgery per Month
   **Unit:** Dollar/Month

62. Total Recovery Cost of Custom=
Custom Accumulative Cost of Hospital Stay + Custom Accumulative Cost of Rehab Stay 
+ Custom Accumulative cost of Home Recovery  
**Unit:** Dollar  
**Comment:** Total accumulative recovery cost for custom

63. Insurance Coverage of Total Cost for Custom= 
Custom Total Cost of the Entire Process* Coverage of Insurance Bundled Payments for CIM  
**Unit:** Dollar

64. OTS Accumulative Cost of Hospital Stay= 
INTEG (OTS Hospital $, 0)  
**Unit:** Dollar

65. Custom Home $=  
Custom Cost of Rehabilitation at Home per Month  
**Unit:** Dollar/Month

66. Custom Readmission=  
Custom Cost of Readmission per Month  
**Unit:** Dollar/Month

67. Custom Rehab $=  
Custom Cost of Rehab Stay per Month  
**Unit:** Dollar/Month

68. Insurance Coverage of Total Cost for OTS=  
Insurance Coverage for OTS*OTS Total Cost of the Entire Process  
**Unit:** Dollar

69. OTS Accumulative $ of Revision=  
INTEG (OTS Revision, 0)  
**Unit:** Dollar

70. Percentage of Home Discharge for OTS=  
100* XIDZ (Rate of OTS Discharge to Home, Rate of OTS Discharge to Rehab, 0)  
**Unit:** Dmnl

71. Percentage of Readmitted Custom Patients=  
100* XIDZ (Custom Patients Readmitted, Custom Patients Recovering at Home, 0)  
**Unit:** Dmnl

72. OTS Accumulative Cost of Procedures=
(OTS Accumulative Number of Patients)*(OTS Cost of Surgery + OTS Product Cost)

**Unit:** Dollar  
**Comment:** Total accumulative procedure cost for OTS

73. OTS Accumulative Cost of Home Recovery=

\[
\text{INTEG (OTS Home $, 0)}
\]

**Unit:** Dollar

74. OTS Revision=

OTS Cost of Revision Surgery per Month

**Unit:** Dollar/Month

75. Percentage of Readmitted OTS Patients=

\[
100^* \text{XIDZ (OTS Patients Readmitted, OTS Patients Recovering at Home, 0)}
\]

**Unit:** Dmnl

76. OTS Total Cost of the Entire Process=

OTS Accumulative $ of Readmission + OTS Accumulative $ of Revision + Total Recovery Cost of OTS + OTS Accumulative Cost of Procedures

**Unit:** Dollar  
**Comment:** Total cost including cost of procedure, recovery, readmission, and revision surgery

77. Custom Home Recovery Complete=

Custom Discharged to Home or with Home Health Care/Custom Duration of Recovery at Home

**Unit:** Implants/Month

78. Initial OTS Performance=

OTS Functioning*(1-OTS Liftoff)

**Unit:** Dmnl  
**Comment:** Implant liftoff has negative impact on performance

79. OTS Learning Curve Strength=

\[
\text{LN (1+OTS Performance Improvement per Doubling of Cooperation)/LN(2)}
\]

**Unit:** Dmnl  
**Comment:** Learning curve formulation, John D. Sterman, Business Dynamics (2000), Chapter 9

80. Effect of Coop on OTS Performance=

(Surgeon and Mfg Coop on OTS/Initial Number of OTS Implants)^OTS Learning Curve Strength

**Unit:** Dmnl
Comment: Learning curve formulation, John D. Sterman, Business Dynamics (2000), Chapter 9

81. OTS Duration of Recovery at Home=
   Time to Recover Completely after OTS Surgery*Effect of OTS performance on Recovery
   Unit: Month
   Comment: Effect of implant performance is considered for home recovery

82. OTS Duration of staying at Rehab=
   OTS Average Rehab Stay*Effect of OTS performance on Recovery
   Unit: Month
   Comment: Effect of implant performance is considered for rehab recovery

83. Effect of OTS performance on Recovery=
   1-(OTS Performance-Initial OTS Performance)
   Unit: Dmnl

84. OTS Home Recovery Complete=
   OTS Discharged to Home or with Home Health Care/OTS Duration of Recovery at Home
   Unit: Implants/Month

85. Surgeon and Mfg Coop on OTS=
   INTEG (OTS Purchase Rate, Initial Number of OTS Implants)
   Unit: Implants

86. Custom Duration of Recovery at Home=
   Time to Recover Completely after Custom Surgery*Effect of Custom performance on Recovery
   Unit: Month
   Comment: Effect of implant performance is considered for home recovery

87. OTS Patient Outcome=
   SMOOTH3 (OTS Performance, Total Duration of OTS Recovery)
   Unit: Dmnl
   Comment: OTS patient outcome considering the duration of recovery

88. Custom Duration of staying at Rehab=
   Custom Average Rehab Stay*Effect of Custom performance on Recovery
   Unit: Month
   Comment: Effect of implant performance is considered for rehab recovery

89. OTS Purchase Rate=
   Patients Using OTS
   Unit: People/Month
90. Custom Performance=
Min ((Initial Custom Performance) * Switch for Experience Effect on Performance*Effect of Cooperation on Custom Implant Performance+ (Initial Custom Performance) * (1-Switch for Experience Effect on Performance)*Effect of Cooperation on Custom Implant Performance, 1)

**Unit:** Dmnl

**Comment:** Implant performance considering the initial performance and improvement in the performance due to the cooperation of manufacturers and surgeons

91. Initial Custom Performance=
Custom Functioning*(1-Custom Liftoff)

**Unit:** Dmnl

**Comment:** Implant liftoff has negative impact on performance

92. OTS Performance=
Min ((Initial OTS Performance * Effect of Coop on OTS Performance), 1)

**Unit:** Dmnl

**Comment:** Implant performance considering the initial performance and improvement in the performance due to the cooperation of manufacturers and surgeons

93. Effect of Custom performance on Recovery=
1-(Custom Performance-Initial Custom Performance)

**Unit:** Dmnl

94. Effect of Cooperation on Custom Implant Performance=
(Surgeon and Mfg Cooperation on CIM/Initial Number of Custom Implants)^Learning Curve Strength

**Unit:** Dmnl

**Comment:** Learning curve formulation, John D. Sterman, Business Dynamics (2000), Chapter 9

95. Surgeon and Mfg Cooperation on CIM=
INTEG (Custom Purchase Rate, Initial Number of Custom Implants)

**Unit:** Implants

96. Surgeon Adoption Ratio=
Surgeon Adopters/Total Orthopedic Surgeon Population

**Unit:** Dmnl

97. Rate of OTS Discharge to Rehab =
Patients Undergoing OTS Implant*(1-Rate of patients discharge to home after OTS surgery)/Time to Decide on Home Discharges

**Unit:** Implants/Month

**Comment:** Rate of patients discharge to either rehab or nursing facility after OTS surgery
98. Time to Decide on Home Discharge from Rehab =
   Custom Average Rehab Stay
   **Unit:** Month

99. Rate of OTS Discharge to Home =
   Patients Undergoing OTS Implant * Rate of patients discharge to home after OTS surgery / Time to Decide on Home Discharges
   **Unit:** Implants/Month
   **Comment:** Rate of patients discharge to either home or home with health care after OTS surgery

100. Time to Decide on Home Discharge from OTS Rehab =
    OTS Average Rehab Stay
    **Unit:** Month

101. Number of Patients Adopting Custom from Surgeons Recommendation =
    SMOOTH3 (Surgeon patient contact * Surgeons Recommendation Effectiveness on Patients for Custom, Time to make a decision)
    **Unit:** Implants/Month
    **Comment:** Surgeons recommendation effectiveness and surgeon patient contact rate are two driving factors for patients to adopt the new product from surgeons recommendation

102. Manufacturer Willingness to Produce Custom =
    DELAY3 (Ratio of Patient Using Custom, Delay for Manufacturers to React to the Market Share to Adopt the new Technology)
    **Unit:** Dmnl
    **Comment:** Fragmented industry/market is a market that none of the players have enough share to dominate the market. Meaning no major player controlling everything. By increase in the number of patients using custom implants, more manufacturers willing to produce custom after associated time delay

103. Ratio of Patient Using Custom = ACTIVE INITIAL (XIDZ (Patients Using Custom, Patients Using OTS + Patients Using Custom, 0), 0.05)
    **Unit:** Dmnl

104. Percentage of Readmitted OTS Patients to all Readmitted Patients =
    100 * XIDZ (OTS Patients Readmitted, Custom Patients Readmitted + OTS Patients Readmitted, 0)
    **Unit:** Dmnl

105. Percentage of OTS Patients Undergone Revision Surgery to all Revision Surgeries =
    100 * XIDZ (OTS Patients Undergone Revision Surgery, Custom Patients Undergone Revision Surgery + OTS Patients Undergone Revision Surgery, 0)
**Unit:** Dmnl

106. Percentage of Patients Using Custom =
   \( \text{XIDZ} \times (100 \times \text{Patients Using Custom, Rate of Incoming Patients, 0}) \)
   **Unit:** Dmnl

107. Percentage of Patients Using OTS =
   \( \text{XIDZ} \times (100 \times \text{Patients Using OTS, Rate of Incoming Patients, 0}) \)
   **Unit:** Dmnl

108. Rate of Reverting Back to OTS =
   \[ \text{IF THEN ELSE} \ (\text{Custom Patient Outcome} > \text{OTS Patient Outcome}, 0, \text{Surgeon Adopters} \times (1 - \text{Relative Performance of Custom over OTS}) / \text{Time to Revert} \) \]
   **Unit:** Surgeon/Month
   **Comment:** If custom patient outcome is smaller than the OTS patient outcome then larger rate of the surgeons who adopt custom implants before would revert back to OTS.

109. Surgeons Adoption Rate =
   \[ \text{IF THEN ELSE} \ (\text{Coverage of Insurance Bundled Payments for CIM} \geq \text{Insurance Coverage for OTS}, \text{Potential Surgeons Adopters} \times \text{Relative Performance of Custom over OTS}) / \text{Time to make a decision} \]  
   **Unit:** Surgeon/Month
   **Comment:** Insurance policies are one of the driving factors for surgeons to become adopters of the new product. In this case if the insurance coverage for custom becomes equal or greater than the coverage for OTS then surgeons would adopt the new product easier. If the insurance coverage for custom is smaller than the coverage for OTS, then that would impact the surgeons’ adoption. Another driving factor is the relative performance of the new product which would impact the surgeons’ decision on adopting the new product.

110. Custom Purchase Rate =
   \( \text{Patients Using Custom} \)
   **Unit:** Implants/Month

111. Total Cost of the Entire System for Both Methods =
   \( \text{Custom Total Cost of the Entire Process} + \text{OTS Total Cost of the Entire Process} \)
   **Unit:** Dollar

112. Custom RAR =
   \( \text{Readmission Rate} \times (1 - \text{Custom Patient Outcome}) \)
   **Unit:** Dmnl
   **Comment:** Readmission Rate (RAR) is based on the rate from literature and patient outcome in such a way if the outcome of patients improves RAR would decrease
113. Custom RSR=
    Revision Surgery Rate*(1-Custom Patient Outcome)
    Unit: Dmnl
    Comment: Revision Surgery Rate (RSR) is based on the rate from literature and patient outcome in such a way if the outcome of patients improves RSR would decrease

114. Patients Using Custom=
    DELAY3 (Rate of Incoming Patients*Fraction of Patients Willing to Use Custom, Waiting time)
    Unit: Implants/Month
    Comment: Rate of patients undergo custom surgery including waiting time delay

115. Patients Using OTS=
    DELAY3 (Rate of Incoming Patients*(1-Fraction of Patients Willing to Use Custom), Waiting time)
    Unit: Implants/Month
    Comment: Rate of patients undergo OTS surgery including waiting time delay

116. Fraction of Patients Willing to Adopt Custom=
    XIDZ (Number of Patients willing to adopt Custom, Number of Patients in Waiting List for Knee Replacement + Number of Patients willing to adopt Custom, 0)
    Unit: Dmnl
    Comment: Relative ratio of patients willing to adopt custom implants to patients in the waiting list for knee replacement

117. Number of Patients in Waiting List for Knee Replacement=
    Patients Deciding on Knee Replacement Method/Waiting time
    Unit: Implants/Month

118. Fraction of Patients Willing to Use Custom=
    ACTIVE INITIAL (IF THEN ELSE (Switch to Block Custom Surgery=1, Coverage of Insurance Bundled Payments for CIM*Fraction of Patients Willing to Adopt Custom, 0), 0, 0.05)
    Unit: Dmnl
    Comment: Fraction of patients willing to adopt custom decide to undergo custom implants surgery based on the insurance policy to cover custom implants

119. Learning Curve Strength=
    LN (1+Custom Performance Improvement per Doubling of Cooperation)/LN(2)
    Unit: Dmnl
    Comment: Learning curve formulation, John D. Sterman, Business Dynamics (2000), Chapter 9

120. Custom Patient Outcome=
SMOOTH3 (Custom Performance, Total Duration of Custom Recovery)  
**Unit:** Dmnl  
**Comment:** Custom patient outcome considering the duration of recovery

| 121. | OTS Liftoff=  
|      | (OTS Condyle liftoff in early flexion + OTS Condyle liftoff in late flexion) / 2  
|      | **Unit:** Dmnl  
|      | **Comment:** Average of early flexion and late flexion liftoff

| 122. | OTS Functioning =  
|      | (OTS Range of Motion + OTS Axial Rotation) / 2  
|      | **Unit:** Dmnl  
|      | **Comment:** Average of the range of motion and axial rotation

| 123. | Custom Functioning=  
|      | (Custom Range of Motion + Custom Axial Rotation) / 2  
|      | **Unit:** Dmnl  
|      | **Comment:** Average of the range of motion and axial rotation

| 124. | Custom Liftoff=  
|      | (Custom Condyle liftoff in early flexion + Custom Condyle liftoff in late flexion) / 2  
|      | **Unit:** Dmnl  
|      | **Comment:** Average of early flexion and late flexion liftoff

| 125. | Rate of OTS Revision Surgeries in 3 Years =  
|      | DELAY3 (Patients Using OTS*OTS RSR, "3 Year Time period")  
|      | **Unit:** Implants/Month

| 126. | Rate of Custom Revision Surgeries in 3 Years=  
|      | DELAY3 (Patients Using Custom*Custom RSR, "3 Year Time period")  
|      | **Unit:** Implants/Month

| 127. | Rate of Custom Readmission in 90 days=  
|      | DELAY3 (Patients Using Custom*Custom RAR, "90 Days Time Period")  
|      | **Unit:** Implants/Month

| 128. | Rate of OTS Readmission in 90 days=  
|      | DELAY3 (Patients Using OTS*OTS RAR, "90 Days Time Period")  
|      | **Unit:** Implants/Month

| 129. | OTS RAR=  
|      | (1-OTS Patient Outcome)*Readmission Rate  
|      | **Unit:** Dmnl
Comment: Readmission Rate (RAR) is based on the rate from literature and patient outcome in such a way if the outcome of patients improves RAR would decrease

130. OTS RSR =
Revision Surgery Rate*(1-OTS Patient Outcome)
Unit: Dmnl
Comment: Revision Surgery Rate (RSR) is based on the rate from literature and patient outcome in such a way if the outcome of patients improves RSR would decrease

131. Patients Undergoing Custom Implant= INTEG (Patients Using Custom-Rate of Custom Discharge to Home-Rate of Custom Discharge to Rehab, 0)
Unit: Patients
Comment: Patients undergo custom surgery

132. Patients Undergoing OTS Implant= INTEG (Patients Using OTS-Rate of OTS Discharge to Home-Rate of OTS Discharge to Rehab, 0)
Unit: Patients
Comment: Patients undergo OTS surgery

133. Rate of Custom Discharge to Rehab=
Patients Undergoing Custom Implant*(1-Rate of patients discharge to home after Custom Surgery)/Time to Decide on Home Discharges
Unit: Implants/Month
Comment: Rate of patients discharge to either rehab or skilled nursing facility after custom surgery

134. Rate of Custom Discharge to Home=
Patients Undergoing Custom Implant*Rate of patients discharge to home after Custom Surgery/Time to Decide on Home Discharges
Unit: Implants/Month
Comment: Rate of patients discharge to either home or home with health care after custom surgery

135. OTS Patients Undergone Revision Surgery=
INTEG (Rate of OTS Revision Surgeries in 3 Years, 0)
Unit: Patients

136. Custom Patients Undergone Revision Surgery=
INTEG (Rate of Custom Revision Surgeries in 3 Years, 0)
Unit: Patients

137. Custom Patients Readmitted=
INTEG (Rate of Custom Readmission in 90 days, 0)
Unit: Patients
138. OTS Patients Readmitted=
   INTEG (Rate of OTS Readmission in 90 days, 0)
   **Unit:** Patients

139. Cost of recovery for Custom per Patient=
   DELAY1 (Cost of Hospitalization in Hospital for Custom + Cost of Hospitalization in Rehab or Nursing Facility for Custom + Cost of Rehabilitation at Home or with Health Care for Custom, Total Duration of Custom Recovery)
   **Unit:** Dollar/Patients
   **Comment:** Total cost per patient for custom implant recovery

140. Cost of Recovery for OTS per Patient=
   DELAY1 (Cost of Hospitalization in Hospital for OTS + Cost of Hospitalization in Rehab or Nursing Facility for OTS + Cost of Rehabilitation at Home or with Health Care for OTS, Total Duration of OTS Recovery)
   **Unit:** Dollar/Patients
   **Comment:** Total cost per patient for OTS implant recovery

141. Initial Early Adopters=
   INITIAL(Total Orthopedic Surgeon Population *Fraction of Surgeons willing to adopt)
   **Unit:** Surgeon

142. Surgeon Adopters=
   INTEG (Surgeons Adoption Rate - Rate of Reverting Back to OTS, Initial Early Adopters)
   **Unit:** Surgeon

143. Total Orthopedic Surgeon Population=
   (1 + Net Orthopedic Surgeon Population Increase) * Initial Orthopedic Surgeon Population
   **Unit:** Surgeon

144. Probability of Contacts with Adopters=
   Surgeon Adopters/Total Orthopedic Surgeon Population
   **Unit:** Dmnl

145. Surgeons NOT Willing to Adopt=
   INTEG (Rate of Reverting Back to OTS + Surgeons Not Interested-Surgeons Becoming Interested, Initial surgeons NOT willing to adopt)
   **Unit:** Surgeon

146. Potential Surgeons Adopters=
   INTEG (Surgeons Becoming Interested-Surgeons Not Interested-Surgeons Adoption Rate, 0)
   **Unit:** Surgeon
147. Initial surgeons NOT willing to adopt =
   \[
   \text{INITIAL(Total Orthopedic Surgeon Population} \times (1 - \text{Fraction of Surgeons willing to adopt})
   \]
   \text{Unit: Surgeon}

148. Surgeons Not Interested =
   \[
   (1 - \text{Relative Performance of Custom over OTS}) \times \text{Potential Surgeons Adopters/Time to make a decision}
   \]
   \text{Unit: Surgeon/Month}
   \text{Comment: Surgeons not interested in using custom implants due to the relative performance of the implants over the decision time}

149. Relative Performance of Custom over OTS =
   \[
   \frac{\text{Custom Patient Outcome}}{\text{Custom Patient Outcome} + \text{OTS Patient Outcome}}
   \]
   \text{Unit: Dmnl}

150. Social Awareness =
   \[
   \text{Patient to Patient Contact Rate} \times \text{(Custom Patients Recovering at Home)}
   \]
   \text{Unit: Implants/Month}

151. Number of Patients Adopting Custom from General Awareness =
   \[
   \text{Patients Becoming Interested in Custom} \times \text{Adoption Fraction}
   \]
   \text{Unit: Implants/Month}

152. Number of Patients willing to adopt Custom =
   \[
   \text{Number of Patients Adopting Custom from General Awareness} + \text{Number of Patients Adopting Custom from Surgeons Recommendation}
   \]
   \text{Unit: Patients/Month}
   \text{Comment: Total number of patients willing to adopt due to social awareness and surgeons' recommendation}

153. Custom Patients Recovering at Home =
   \[
   \text{INTEG (Custom Home Recovery Complete, 0)}
   \]
   \text{Unit: Patients}

154. OTS Duration of Hospitalization =
   \[
   \text{OTS Average Hospital Stay}
   \]
   \text{Unit: Month}

155. Custom Duration of Hospitalization =
   \[
   \text{Custom Average Hospital Stay}
   \]
   \text{Unit: Month}

156. OTS Patients Recovering at Home =
INTEG (OTS Home Recovery Complete, 0)

**Unit:** Patients

157. **Total Duration of OTS Recovery** =
   OTS Duration of Hospitalization + OTS Duration of Recovery at Home + OTS Duration of staying at Rehab

   **Unit:** Month

158. **Cost of Hospitalization in Hospital for OTS** =
   Average Cost of Hospital Stay * OTS Duration of Hospitalization

   **Unit:** Dollar/Patients

   **Comment:** Cost per patient for hospital stay for OTS implant patients

159. **OTS Cost of Surgery** =
   (Cost of Surgeon + Cost of Operations Room) * Time of OTS Procedure

   **Unit:** Dollar/Patients

   **Comment:** Cost of surgery includes cost of surgeon, cost of operation room and time of the procedure

160. **Time of Custom Procedure** =
   Time of OTS Procedure - Time reduction during the procedure

   **Unit:** Hour/Patients

161. **Custom Cost of Surgery** =
   (Cost of Operations Room + Cost of Surgeon) * Time of Custom Procedure

   **Unit:** Dollar/Patients

   **Comment:** Cost of surgery includes cost of surgeon, cost of operation room and time of the procedure

162. **Total Duration of Custom Recovery** =
   (Custom Duration of Hospitalization + Custom Duration of Recovery at Home + Custom Duration of staying at Rehab)

   **Unit:** Month

163. **Cost of Hospitalization in Hospital for Custom** =
   Average Cost of Hospital Stay * Custom Duration of Hospitalization

   **Unit:** Dollar/Patients

   **Comment:** Cost per patient for hospital stay for custom implant patients

164. **Patients Becoming Interested in Custom** =
   Probability of Contact with Custom Patients Discharged to Home * Social Awareness

   **Unit:** Implants/Month

   **Comment:** Patients becoming interested in custom implants by having contact with patients who previously underwent the custom implant surgery
In the absence of published literature, some of the parameters are estimated using the partial calibration method (Homer 2012, Hosseinichimeh, Rahmandad et al. 2015, Ghaffarzadegan, Ebrahimiand et al. 2016). The calibrated model is then tested to compare the number of patients at different stages, including surgery, hospitalization and recovery, readmission, and revision surgery, to the aggregated historical data from 1990 to 2012.

### 3-2.3.3. Model Calibration

While many of the model parameters are obtained from various existing datasets, there are no comprehensive data available for some parameters. In this situation, calibrating the model statistically to data would be a helpful method to estimate the unknown parameters. To do so, partial model calibration method (Homer 2012) is used to calibrate different parts of the model separately. This method decreases the overfitting chances by providing robust estimates. For some of the unknown parameters, calibration cannot be done; thus, several assumptions have been made based on empirical knowledge. Therefore, conducting sensitivity analysis is essential to test the sensitivity of the model to our assumptions.

#### 3-2.3.3.1 Unknown Parameters Calibration

Table 3-4 provides information on the calibrated model parameters.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Calibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient Increase Rate</td>
<td>0.0069</td>
<td>Calibration 1</td>
</tr>
<tr>
<td>Revision Surgery Rate</td>
<td>0.0875</td>
<td>Calibration 2</td>
</tr>
</tbody>
</table>

Calibration 1:
• Input: Rate of incoming patients based on the historical data from different resources on Number of patients undergone primary knee replacement presented in Table 3-1.
• Payoff function: Maximize the fit between the historical data and the simulation of patients decided to have knee replacement.
• Result: Finding the unknown parameter, Patient Increase Rate (Table 3-4).
Figure 3-4: Calibration 1, containing: a) sub-model structure, b) simulated outcome

Calibration 2:

- **Input**: Rate of OTS revision surgeries in 3 years after primary knee replacement. Data is available from different resources on Number of patients undergone revision knee replacement presented in Table 3-1.
- **Payoff function**: Maximize the fit between the historical data and the simulation of patients undergone revision procedures.
- **Result**: Finding the unknown parameter, Revision Surgery Rate (Table 3-4).

Sub-Model Structure (Estimated parameter is in green)
3-2.3.3.2 Unknown Parameters Assumptions

Table 3-5 provides information on the parameter assumptions.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Patients Undergo Primary TKA at first month of 2017</td>
<td>110760</td>
<td>Estimated number of patients in 2017. (Kurtz, Ong et al. 2011)</td>
</tr>
<tr>
<td>OTS Average Rehab Stay</td>
<td>4 Days</td>
<td>Rehab stay for patients with OTS implants is between 2 to 7 days. Assumed 4 days.</td>
</tr>
<tr>
<td>Custom Average Rehab Stay</td>
<td>3 Days</td>
<td>Rehab stay for patients with Custom implants is between 2 to 5 days. Assumed 3 days.</td>
</tr>
<tr>
<td>Surgeons Recommendation Effectiveness on other Surgeons for Custom Implants</td>
<td>30%</td>
<td>Presents the effectiveness of recommendation of early adopter surgeons on the surgeons who are becoming interested in using custom implants.</td>
</tr>
<tr>
<td>Fraction of Surgeons willing to Adopt Custom (Early Adopters)</td>
<td>1%</td>
<td>The number of early adopter surgeons assumed as 1% of total surgeons population (&lt;300).</td>
</tr>
<tr>
<td>Surgeons to Adopters (Surgeons) Contact Rate</td>
<td>10/Month</td>
<td>It is assumed each surgeon has contact with 10 adopter surgeons each month.</td>
</tr>
<tr>
<td>Time to Adopt Custom (for Surgeons)</td>
<td>1 year</td>
<td>Presents the time period takes for a surgeons to be convinced and adopt the new technology after comparing patient outcome of the old and new products.</td>
</tr>
<tr>
<td>Parameters</td>
<td>Value</td>
<td>Definition</td>
</tr>
<tr>
<td>----------------------------------------------------------------------------</td>
<td>----------------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Time to Revert (from Custom for Surgeons)</td>
<td>6 months</td>
<td>Presents the time period takes for adopter surgeons to revert to the old product when they don’t see any improvements in patient outcome.</td>
</tr>
<tr>
<td>Time for Custom Reps to Adjust (their interests)</td>
<td>3 months</td>
<td>Presents the time takes for sales force to switch to promote new product after manufacturers turned their interests.</td>
</tr>
<tr>
<td>Surgeons Recommendation Effectiveness on Patients for Custom Implants</td>
<td>80%</td>
<td>Presents the effectiveness of recommendation of surgeons on their patients who are going to have knee replacement procedure.</td>
</tr>
<tr>
<td>Patient-Patient contact Rate</td>
<td>5 /year</td>
<td>It is assumed each patient has contact with 5 other patients who have done knee replacement before regarding their procedure outcome each year.</td>
</tr>
<tr>
<td>Adoption Fraction of the Patients due to Awareness</td>
<td>0.05</td>
<td>Presents the fraction of the new patients willing to adopt the new product due to their contacts with other patients who are using the new products</td>
</tr>
<tr>
<td>Custom Design &amp; Performance Improvement per Doubling of Cooperation</td>
<td>0.05 / year</td>
<td>5% improvement is assumed for doubling the CIM implants manufacturers and surgeons cooperation based on the learning curve formulation of Sterman (Sterman 1994, Sterman 2000).</td>
</tr>
<tr>
<td>OTS Design &amp; Performance Improvement per Doubling of Cooperation</td>
<td>0.025 / year</td>
<td>2.5% increase is assumed for doubling the cooperation of manufacturers and surgeons (Sterman 1994, Sterman 2000). (Half the custom implants improvement rate)</td>
</tr>
<tr>
<td>Multiplication of OTS Product Cost for Custom Implants</td>
<td>1.25</td>
<td>Since the cost of Custom knee implants are very difficult to find, in the model, it is assumed that these implants cost 25% higher than OTS implants (Schrock 2014, Lewis 2015).</td>
</tr>
<tr>
<td>Sales Reps Influence on promoting OTS (initial value)</td>
<td>0.7</td>
<td>The initial which also includes pricing arrangement between hospitals and producers of OTS implants considered as high (O’Connor, Pollner et al. 2016).</td>
</tr>
<tr>
<td>Delay for Manufacturer to React to the Market Share to Adopt New Technology</td>
<td>3 years</td>
<td>Presents the time period takes for the implant manufacturers to switch to new technology when they see an increase in the market share of the new products.</td>
</tr>
</tbody>
</table>
To increase confidence in the model, various validation tests are performed: unit consistency, equation robustness in extreme conditions (Sterman 2000), and behavior validity (Senge and Sterman 1992, Barlas 1996).

3-2.3.4. Model Validation

In this section, we first validate the model by replicating the historical data for OTS implant procedures. In addition to OTS procedures, to show the model robustness, we added custom implant procedures from 1990-2012 and replicated the historical data one more time under that condition. Furthermore, we used the expected number of knee replacement procedures up to 2026 (Kurtz, Ong et al. 2007, Kurtz, Ong et al. 2014, Inacio, Paxton et al. 2017) and tested the model with the estimated data to find the parts of the model that can better represent the reality and the parts that produce more error. Figure 3-6 illustrates the simulation results in comparison with historical and expected future data.

![Graph](image-url)
Availability of OTS and CIM and comparison between incoming patients and simulated outgoing patients

Figure 3-6: Comparing historical data and simulation results from 1990 to 2012 when the OTS procedure is the only available option for patients. Comparing historical data and simulation results from 1990 to 2012 when the OTS and CIM procedures are both available. Based on the assumption that CIM procedure was available during that time to test the model reliability. Comparing expected data and simulation results from 2018 to 2026 when the OTS and CIM procedures are both available.

Concentrating on the physics of the model, which technically is the flow of patients, helped us to replicate the data with high correlation. The simple logical inflows and outflows of the stock variables could officially validate the model.
3-3. Results

_Baseline_

The base case scenario reflects the current market share of CIM implants (less than 5%) (Inc. 2016) and follows the status quo with respect to CIM adoption. The costs of knee replacement procedures are estimated considering the complete procedure, duration of hospitalization and recovery, and numbers of unscheduled readmissions and revision surgeries. These factors are weighed against patient outcomes/functionality for a full cost-benefit analysis. The initial levels of vendor-established contracts with hospitals and surgeons, and natural resistance to adoption of CIM implants as a new product/technology, are considered medium-to-high in the model (O’Connor, Pollner et al. 2016). The coverage of third-party payers’ fixed rate bundled payment programs for CIM procedures define the insurance policy scenarios.

_Simulated Intervention_

Figure 3-7 presents the dynamics of the numbers of readmissions and revision surgeries for all patients under the base scenario and levels of bundled payment coverage of CIM procedures. Considering high variability in costs of knee replacement procedures for several reasons (discussed earlier), and since CIM implants are about 20%-30% more expensive than OTS implants, the fixed rate bundled payments could still cover more than 60% of CIM procedures (Schrock 2014, Lewis
Therefore, we consider three levels of coverage for CIM procedures: 50%, 70%, and 90%. Meanwhile, the insurance coverage for OTS implants remains constant at 90% (Olmos 2010, Lewis 2016, Greengard 2017, Romualdez 2017); it is set at the highest payment reimbursed for CIM in the policy analysis. The base case represents the continuation of the current conditions for CIM implants—being used in around 5% of cases. It could be hypothesized that once coverage for CIM increases to, say, 90%, the coverage rate for OTS could decrease from the status quo. However, the OTS coverage was kept constant, considering a pessimistic situation, because decreases in OTS coverage would be another driver for CIM adoption, resulting in even better performance outcomes than those presented.

Due to uncertainties regarding the levels of coverage of insurance bundled payments for CIM procedures, patient outcomes/functionality, possible improvements in CIM and OTS implants in the future, and relative price of CIM and OTS implants, an online version of the model is developed in an interactive environment, which enables running the model quickly under various user-created scenarios (http://jalali.mit.edu/medical-tech-adoption)—more information in the sensitivity analysis section.

Readmissions and Revision Surgeries

The decisive elements for readmission and revision surgery rates in the model are the initial rates obtained from the literature (Ramos, Wang et al. 2014, AJRR 2018, NJR 2018), which change overtime with patient outcomes/functionality after primary knee replacements. Patient outcomes/functionality are determined by standardizing range of motion and axial rotation for each type of implant to healthy knee performance, along with the average rate of condyle lift-off in
early and late flexion for each type of implant (Schwarzkopf, Brodsky et al. 2015, Zeller, Sharma et al. 2016). Figure 3-7 illustrates the percentage change in the number of readmitted patients within 90 days and the number of revision surgeries within 3 years after primary knee replacements for different levels of coverage of insurance bundled payment programs for CIM. The highest percentage of patients who were readmitted or underwent revision surgeries occurs in the base case, which represents the current scenario for CIM. The lowest numbers of readmissions and revision surgeries occurs for 90% CIM coverage, in which, by 2026, the number of readmissions and revision surgeries could be reduced by approximately 62% (285,962) and 39% (44,157), respectively. It is worth mentioning that readmissions and revisions are two independent events with different financial implications, because the costs for revision surgeries are much higher, as indicated in Figure 3-8.

![Graph showing percentage change in readmissions and revision surgeries](image)

Figure 3-7: Percentage of patients readmitted (OTS and CIM) within 90 days and percentage of patients undergoing revision surgeries (OTS and CIM) within 3 years after primary procedures under different levels of coverage of insurance bundled payment programs for CIM procedures. Three insurance policies, covering CIM implants at 50%, 70%, and 90%, in addition to the base case are presented. The highest percentage of readmissions and revision surgeries occur in the base case. As the CIM coverage rate increases, the number of readmissions and revision surgeries decrease.

**Cost Effectiveness**
Figure 3-8 shows the total cumulative cost estimates by the year 2026. It compares the cumulative costs of knee replacement procedures for both OTS and CIM under different coverage for CIM implants. The total cumulative costs include costs for the procedure (product, surgeons, and operating rooms), recovery (in hospital, home, nursing facility, and rehab), 90-day readmissions, and 3-year revision surgeries. None of the scenarios would cost more than the base case, due to the higher long-term costs associated with OTS implants. Healthcare costs for the stakeholders for items such as recovery, readmissions, and revision surgeries in CIM are lower than those for OTS. These lower costs compensate for the higher costs of CIM implants relative to the cost of OTS. According to Figure 3-8, the higher the coverage rate for CIM, the higher the cost savings for every scenario. The highest cumulative savings of approximately $38 billion (about 6% of the total costs) could be achieved under 90% coverage for CIM for all the stakeholders together by 2026.

**Adoption**

Figure 3-9 illustrates that an increase in the coverage of insurance bundled payment programs for CIM would catalyze the adoption of these implants by patients. The coverage of insurance bundled payment programs at 70% and 90% greatly increase adoption rates because more hospitals, surgeons, and incoming patients are willing to opt for CIM implants. The sudden increases in CIM adoption at 70% and 90% coverage rates are driven by the higher number of incoming patients willing to use CIM due to perceived better performance and financial feasibility. Under these coverage rates, a higher number of surgeons and patients will be willing to adopt CIM. After the initial rapid increases, the system stabilizes, and the adoption rate increases smoothly.
Total Cost per Patient

Figure 3-10 shows nationwide average total costs per patient under different policies within 3 years of primary knee replacement. Total costs include the costs of the procedure, recovery, readmission, and revision surgery. Figure 3-10 indicates that 90% coverage of insurance bundled payment programs for CIM has better potential to reduce the cost per patient over time due to the performance improvements resulting from CIM implants. Since recovery time, readmission, and revision surgery rates are related to patient outcomes/functionality, cost savings can be achieved with only 50% adoption, and the savings significantly increase for higher coverage rates: $1,600 per patient for 70% and $2,200 for 90%.
Figure 3-8: Total cumulative costs for all the stakeholders in 2026 (based on the dollar value in 2018) under different coverage policies for CIM implants. The base case represents the current conditions for CIM implant coverage of 5%. Three coverage rates are considered, 50%, 70%, and 90%, for CIM implants from 2018 to 2026. Each bar stacks up several boxes, which represent (from bottom to top) OTS surgery costs, OTS recovery costs, OTS readmission costs (the bold line), OTS revision surgery costs, CIM surgery costs, CIM recovery costs, CIM readmission costs (the bold line), and CIM revision surgery costs. The differences among the bars illustrate the amount of savings that can be achieved under each coverage rate for CIM implants. This figure indicates that shortening recovery period along with decreasing revision surgeries can have the most positive impacts on cost savings.

Figure 3-9: Patient adoption rate. The initial value of adoption is equal to the current market share of CIM implants (less than 5%). Three levels of coverage of insurance bundled payment programs for CIM implants, 50%, 70%, and 90%, are presented. An increase in insurance coverage raises adoption rates of CIM implants. The base line indicates the base case, which shows the current conditions for CIM. Sharp increases under the 70% and 90% coverage rate scenarios are due to increases in the initial number of patients willing to adopt CIM.

**Surgery Time Savings**

CIM procedures can save time for hospitals, not only because of shorter recovery, but also because of shorter procedure time (Buch 2014, Bozic, Kamath et al. 2015, Schwarzkopf, Brodsky et al. 2015, Haas and Kaplan 2017). Figure 3-11 represents the plots of nationwide total surgery time savings per month under different levels of coverage of insurance bundled payment programs for CIM procedures. Further investigations are required to analyze the time savings from an additional revenue standpoint, since the cost of staff, overhead, operating rooms, and the number of patients receiving the service vary among providers. According to Figure 3-11, the most surgery time savings could be achieved through a 90% coverage rate, compared with the base case. The
cumulative surgery time saved could reach over 45,000 hours per month for knee replacements nationwide. It is notable that the plots in Figure 3-9 (adoption) and Figure 3-11 follow a similar pattern. This similarity confirms that when more patients adopt CIM implants, more time savings per surgery can be achieved.
Figure 3-10: Total cost per patient under different coverage policies for CIM implants. This figure shows the trend of nationwide average total cost per patient within 3 years of primary TKA (based on the dollar value in 2018). The savings under 90% CIM coverage rate are higher than those in other scenarios because of CIM’s potential for improvements in patient outcomes/functionality and consequent reductions in recovery time, readmission rate, and revision surgery rate.

Figure 3-11: Surgery time savings per month under different levels of coverage of bundled payment programs for CIM implants. The highest time saving could be achieved under the 90% CIM coverage rate. Understandably, there would be no time savings for the base case. The similarity between the trends of surgery time savings and adoption rates (Figure 3-9) indicates that higher CIM adoption rates could lead to higher time savings per surgery.

3-4. Sensitivity Analysis and Online Simulator Platform

Sensitivity Analysis

To ensure the reliability of our model, a series of sensitivity analysis has been done on the assumed parameters. Sensitivity analyses also illustrated that the simulation outcomes are comparably robust for changes in the assumptions and estimated parameters. For the sensitivity analysis, the values of listed parameters in Table 3-6 change by ±50% under 90% coverage for CIM implants, to investigate the effects on the model outputs (total cost per patient within 3 years (Y1) and percentage of patients using CIM implants (Y2)). In addition, sensitivity analysis results
considering ±50% change in all parameters at the same time are also provided. All the results are presented in Table 3-6.

Table 3-6: Sensitivity Analysis Results on Assumed Model Parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Input</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Change in Parameter</td>
<td>Change in Total $/patient (Y1)</td>
</tr>
<tr>
<td>Surgeons Recommendation Effectiveness on Surgeons for CIM</td>
<td>±50%</td>
<td>±0.32%</td>
</tr>
<tr>
<td>Surgeons to Adopters (surgeons) Contact Rate</td>
<td>±50%</td>
<td>±0.15%</td>
</tr>
<tr>
<td>Time to Make Decision (surgeons to adopt)</td>
<td>±50%</td>
<td>±0.37%</td>
</tr>
<tr>
<td>Surgeons Recommendation-Effectiveness on Patients for CIM</td>
<td>±50%</td>
<td>±0.69%</td>
</tr>
<tr>
<td>CIM Performance Improvement per Doubling the Cooperation</td>
<td>±50%</td>
<td>±0.34%</td>
</tr>
<tr>
<td>OTS Performance Improvement per Doubling the Cooperation</td>
<td>±50%</td>
<td>±0.01%</td>
</tr>
<tr>
<td>Manufacturer Delay to React to the Market share to Adopt New Technology</td>
<td>±50%</td>
<td>±0.34%</td>
</tr>
<tr>
<td>Multiplication of OTS Product Cost for Price of CIM implant</td>
<td>±50%</td>
<td>±8.89%</td>
</tr>
</tbody>
</table>
The results of the sensitivity analyses indicate that the most sensitive parameter for total cost per patient within 3 years (Y1) and percentage of patients using CIM implants (Y2) are “Multiplication of OTS Product Cost for Price of CIM implant” and “Time to Make Decision (surgeons to adopt)” respectively.

Simulation results based on 200 Monte Carlo simulation runs for 50%, 75%, 95%, 100% intervals are provided in Figure 3-12.
b) Sensitivity of patients using CIM and total cost/patient to ±50% change in “Surgeons to Adopters (surgeons) Contact Rate”

c) Sensitivity of patients using CIM and total cost/patient to ±50% change in “Time to Make Decision (surgeons to adopt CIM)”

d) Sensitivity of patients using CIM and total cost/patient to ±50% change in “Surgeons recommendation effectiveness on Patients for CIM”

e) Sensitivity of patients using CIM and total cost/patient to ±50% change in “CIM Performance Improvement per Doubling the Cooperation between Manufacturers and Surgeons”
f)  Sensitivity of patients using CIM and total cost/patient to ±50% change in “OTS Performance Improvement per Doubling the Cooperation between Manufacturers and Surgeons”

g)  Sensitivity of patients using CIM and total cost/patient to ±50% change in “Manufacturer Delay to React to the Market Share to Adopt New Technology”

h)  Sensitivity of patients using CIM and total cost/patient to ±50% change in “Multiplication of OTS Product Cost for Price of CIM Implants”
i) Sensitivity of patients using CIM and total cost/patient to ±50% change in “Time for CIM Sales Force to Adjust (promote CIM implants)”

j) Sensitivity of patients using CIM and total cost/patient to ±50% change in “All the parameters together”

Figure 3-12: Sensitivity Analysis Results

The results illustrate that there could be a change between 3% and 9% if all parameters change by 50%. This can ensure that the model is relatively robust to the changes in all assumed parameters.

*Online Simulator Platform*

To make it easier for users to run the model under different policy conditions without any software requirements, an online version of the model is developed using Forio which is accessible at: [http://jalali.mit.edu/medical-tech-adoption](http://jalali.mit.edu/medical-tech-adoption)
The interface of the online simulator is shown in Figure 3-13. The online model can be simulated for periods of 1 and 3 years, or it can be simulated at once to the final time (2026). This provides the flexibility to incorporate various dynamic policies (by updating model parameters) midway through the simulation run and observe the results. The reset button returns the model to its initial conditions.

There are four parameters available to change in the online simulator:

1) Coverage of Insurance Bundled Payments for CIM: represents the coverage rate for CIM implants 0 and 90%.

2) Relative price of CIM implants to OTS: represents the magnitude of CIM implant price to OTS. The price of CIM can be changed from 0.5 to 3 times of the OTS price.

3) Percentage of performance improvement by year for either CIM or OTS implants: represents the improvement percentage in either procedure per year between 0 and 20% due to the improvement in the design phase.

4) Timesaving per procedure: represents the hours that can be saved by using CIM implant and instruments in each procedure.

The plots in the online simulator show the impacts of changing parameters above on readmission and revision surgery rates, total cost per patient, cumulative time saved for surgeons and hospitals per month, percentage of CIM adoption, and cumulative total costs for both CIM and OTS procedures.
We hope that the outcomes of this study encourage more systematic methods for analyzing the effects and consequences of different policies on the adoption of new knee implant technologies.

3.5. Discussion

Bundled payment programs for total hip and knee arthroplasties are expected to reduce the costs while ensuring the quality of these procedures. These bundled payments focus on costs within 90 days of the surgical procedure and are not designed to impact long-term outcomes or costs. The results of our modeling and analysis indicate that if the coverage of bundled payments for CIM procedures is at 90%, the healthcare system could achieve cumulative savings of $38 billion by 2026.
Joint replacement is a multi-stage process, from pre-procedure preparation to post-operative recovery and avoidance of complications. In the process, various stakeholders have different objectives. Therefore, achieving effective strategies requires a systematic perspective, considering the major factors at all stages of the process and their interconnections, as reflected in the model presented in this work.

We considered an integrated framework for the economic and potential patient outcomes of OTS and CIM knee implants under different scenarios. An adoption rate of CIM implants is driven by surgeons’ recommendations and out-of-pocket surgery cost for patients, which is mainly dependent on the levels of coverage of insurance bundled payment programs for CIM procedures. Higher adoption rates could not only improve some categories of patient outcomes, but also decrease hospital costs, insurance providers’ economic burden, and patients’ out-of-pocket expenditures.

Taking into account the substantial growth in the number of patients needing primary knee replacements, as well as the significant reduction average age of new patients (Weinstein, Rome et al. 2013), the number of revision procedures will grow considerably in the near future. The shrinking number of surgeons available to take care of these increasing volume of patients makes the need to decrease the number of revision procedures even more critical (Iorio, Robb et al. 2008). The results of our analyses indicate that substantial reductions in the number of revision surgeries could be achieved through higher adoption of CIM implants.

Furthermore, CIM implants could significantly reduce 90-day readmissions, procedure times, and recovery after primary knee replacements. Consequently, higher coverage for CIM
procedures could be expected to reduce costs for hospitals and other stakeholders in the entire healthcare system around TKA. We expect that greater attention to the potential benefits of CIM implants would promote personalized healthcare.

It is worth noting that the reimbursement rates have dropped to a flat, narrow range over the past few years. This trend puts some financial constraints on hospitals and service providers. Future modeling studies could examine how several categories of implants and instrumentation manufacturing costs (e.g., liability, R&D, marketing, overhead, and insurance costs) could be incorporated in the final cost of the products. Moreover, future research could compare how advancements in different areas of joint replacement procedures, such as operative techniques, anesthesia, pain management, and outpatient TKA in Ambulatory Surgical Centers could influence patient outcomes.

3-6. Study Limitations

First, the current simulation model, like most models, cannot portray full reality, but the validated model can potentially help uncover complexities in the healthcare system around TKAs. The analyses compare the relative potential of different insurance policies rather than predicting precisely the long-term effect of these policies. Second, the simulation model did not consider indirect costs and delays associated with administrative processes. Indirect costs may include lost wages due to patients’ disability from the procedures. Administrative processes may include delays due to the U.S. Food and Drug Administration (FDA) approval process and bureaucratic burdens of ordering system. All hospital entities have to use FDA-approved medical devices (Christensen and Rybicki 2017); however, FDA regulations for 3D printed medical devices are expected to
increase in the near future, which could put increased pressure on the adoption of these products (Jungling, Wood et al. 2013). In the model, we assumed that the FDA would approve new CIM implant manufacturers and their products within a period of four months. Complexity of ordering system may include selection of implant (partial, total, cruciate retaining, etc.) and transferring the CT data to a manufacturer which can cause bureaucratic burdens and limit the adoption.

We considered performance improvements of CIM implants, the design phase and the use phase during surgery, as a “moving target,” since the evaluation process takes time and may not reflect the latest effects of product modifications on performance (Homer 1987). OTS implants have been on the market for a long time, and 3D printed patient-specific surgical guidance for OTS implants and robotically assisted surgery (Baker, Deehan et al. 2012, O'Connor and Kransdorf 2013, Dai, Scuderi et al. 2014, Hamilton, Burnett et al. 2015, Patil, Bunn et al. 2015, Choi and Ra 2016, Chua and Chui 2016) have enhanced their improvements up to the present; CIM implants were introduced only a few years ago. For this reason, we consider the potentials for improvements of CIM implants in the design phase and the use phase during surgery to be 5% per year: 2.5% higher than OTS. However, to increase our confidence in the model, sensitivity analyses were done on the performance improvement assumptions for each type of implant. According to the sensitivity analysis results presented in the next section, the model is relatively robust to changes in performance improvements. In addition, the online simulator platform, mentioned in the model and sensitivity analysis sections, provides decision-makers with the flexibility to incorporate various performance improvement rates for either type of implant (OTS or CIM), initially or midway through the simulation run, and observe the results.
Outpatient total joint arthroplasty has become more popular in recent years because of the economic benefits due to lower costs associated with reduced length of stay (Aynardi, Post et al. 2014, Lovald, Ong et al. 2014, Vehmeijer, Husted et al. 2018). The Center for Medicare and Medicaid Services removed TKA from inpatient-only list beginning January 2018 (ED.D. 2018). However, according to the American Association of Hip and Knee Surgeons (AAHKS 2017), outpatient TKA should only be utilized for patients who are healthy enough to have a procedure in such settings. The patient should also have an appropriate home support for being discharged with no hospitalization. Similar to any other episode of care, there are advantages and disadvantages associated with outpatient TKA, i.e., reduced costs and discharge on the day of surgery which could lead to either patient satisfaction or dissatisfaction if it causes more complications such as implant failure, stiffness, more readmissions and potentially revision surgeries (Arshi, Leong et al. 2017). In our generic model, we considered that OTS and CIM implants can be used in either inpatient or outpatient setting uniformly, however, if the dynamic changes and more patients become interested in outpatient procedures, the model can be expanded to distinguish between inpatient and outpatient settings.

All these assumptions and limitations notwithstanding, the simulation model facilitates a systematic study to better understand the effects of knee replacement procedure coverage policies. As presented in the previous sections, the model’s accuracy is validated considering these assumptions.
3-7. Conclusion

The goal of the present study was to take a systematic look at the adoption of CIM knee implants. The objective was not to explore how to improve treatment, but rather to perform what-if analyses. The flexible nature of the model lends itself to extending it to study innovative policies and interventions focused on economic burden and patient outcomes when new information becomes available. The model allows decision and policy makers to test different coverage policies based on their preference. For instance, they can consider a dynamic scenario for their coverage rate for CIM procedures based on their initial investment and savings throughout the simulation time. They can also test the effect of time delays on the preparation of the infrastructure. The results may help policymakers consider CIM implants as an attractive option for improving patient outcomes, while reducing the total costs of healthcare associated with TKA. The results could inform decision-making among the Centers for Medicare and Medicaid Services, private insurance providers, and hospitals, spurring them to consider adoption of CIM implants and to offer alternative payment methodologies that would encourage widespread utilization of CIM knee implants.
Chapter 4 - Location allocation optimization model to assess distributed additive manufacturing for biomedical implants: Massachusetts case study

A facility location allocation optimization model is developed to help decision making process for utilization of customized individually made hip and knee implants fabricated onsite of hospitals through additive manufacturing processes in the state of Massachusetts. Customized individually made implants have the potential to improve patient satisfaction and quality of life while reducing post-operative complications. Despite the advantages of customized individually made implants, a careful investigation should be performed to support higher adoption of these products. In this study, several elements such as customized individually made implants relative production cost to conventional/off-the-shelf implants, transportation cost, lead time cost and weighted distance penalty are used to develop a mixed integer programming optimization model. Through a range of specified preferences, the model determines where to locate AM centers,
volume of customized and conventional products, and flow of the products between manufacturing facilities and hospitals. Results from the mixed integer programming model provide insights for decision makers over a range of preferences on economic considerations for customized individually made implants production in the state of Massachusetts which is expandable to a larger region.
4-1. Introduction

Fabrication of customized individually made (CIM) implants, through 3D printing/Additive Manufacturing (AM) processes, that fits the anatomy of every single patient, could contribute to personalized, high quality and economically effective healthcare as discussed in the third chapter. Additively manufactured CIM implants are fabricated by converting a series of 2D scanned images of the patient’s joint to create a 3D model. The 3D model is then used as a template to guide the deposit of powdered material, layer upon layer, to create a final product as a replica of the original joint. This additive manufacturing technology allows the production of personalized implants to improve patient outcomes. The higher adoption of CIM implants can improve patient satisfaction and Health Related Quality of Life (HRQL). On the other hand, CIM implants can provide on-demand production that can lead to more sustainable manufacturing and supply chain cycle.

Most of the biomedical implants are mass produced in fixed sizes and shapes. More than 99% of implants in the United States were coming from six major manufacturers in 2013 (Angrish 2013). As illustrated in the third chapter, it is important to incorporate patients’ anatomy in the design and fabrication processes of biomedical implants to improve patient satisfaction and support sustainable production processes while eliminating trial and error fittings of implants. AM not only can provide mass customization/personalization, raw material efficiency and cleaner production (Kianian 2015), but also can reduce the obsolete inventory of certain sizes which have low demands, that could lead to more material and energy efficiency (Gao and Qin 2016).
According to (Schubert, van Langeveld et al. 2014) medical applications of additive manufacturing are expected to revolutionize the healthcare industry.

On the other hand, 85% of hip and knee replacement are due to Osteoarthritis (Crawford and Murray 1997, Hunter and Felson 2006), the most common type of degenerative joint disease which projected to be the fourth cause of global disability and impacting 9.6% of men and 18% of women – which adds up to around 150 million people worldwide by 2020 (Woolf and Pfleger 2003, Fox and Stephens 2007). International Conference on Harmonization (ICH) guidance asserted that the primary objective of each clinical trial is treatment efficacy with potential primary variables such as safety and measurements related to Quality of Life (QOL) and health economics (ICH-Expert-Group 1998). By linking the QOL to the evaluation of health condition and treatment, Patient Reported Outcome (PRO) and Health Related Quality of Life (HRQL), as one of the subgroups of PRO, have been widely used by healthcare industry to asses a treatment efficacy and patient satisfaction over the past decade. Health Related Quality of Life, as one of the subcategories of PRO, can present patients health evaluation and treatment satisfaction as daily life, wellbeing and functioning (Acquadro, Berzon et al. 2003). Knee Injury and Osteoarthritis Outcome Score (KOOS 2012) and Knee Society Score (KSS 2012) are the two most common assessment methods to evaluate patients’ post-operative outcome scores after 6 months, 1 and 2 years for the knee replacement procedures. Results specifically illustrate that patients using CIM implants experienced substantial improvements across all five domains of the KOOS scoring system including pain, symptoms, activity of daily living, recreation, and quality of life. For the KSS scoring system, improvements have been reported in objective, satisfaction, and functional scores. Reports (Dunbar, Richardson et al. 2013, Choi and Ra 2016) show that 17% of patients were not
satisfied after Off-The-Shelf (OTS)/conventional implant knee replacement, while the satisfaction rate for CIM patients is 92% (Sunshine 2016, Bear 2017).

Considering the benefits of the CIM implants, these products have not been widely adopted. One of the barriers discussed in chapter three, is the willingness of manufacturers to adopt/switch to the new technology. This requires careful tradeoff investigation of establishing a distributed additive manufacturing network to meet the required demand for CIM implants fabricated by AM technology. This study is proposing a new avenue to explore system level cost and economic feasibility for fabricating hip and knee implants in the state of Massachusetts which can be expanded to the entire country. Using a facility location allocation model under several demand scenarios, we analyze the costs associated with the proposed facility allocation policies. The mixed integer programming (MIP) model in this study is multiple commodities, single period, capacitated, and deterministic by considering several demand scenarios which solved by Gurobi solver in the Python environment. Explicitly, the output of the MIP model recommends the optimal number of AM centers to be established, the number of products to be ordered from conventional implant supplier or AM center, by minimizing the overall cost (e.g., capital cost, production cost, transportation cost, and lead time) and weighted distance while maximizing the network coverage. Specifically, the generalizable contributions of this work include:

- A new focus on and study of flexibility in CIM implants production to meet the required demand of customized hip and knee implants in the state of Massachusetts, which allows for system level cost and weighted distance minimization.
• The demonstration of the system level costs of utilizing AM technology to fabricate CIM implants in the state of Massachusetts under different scenarios.

• The analysis of different demand scenarios, contradictory nature of the cost parameters, distance priorities and relative cost of AM to conventional products to provide insightful results for decision makers.

The rest of this chapter is organized as follows: Section 4-2 reviews the existing literature related to the facility location allocation; Section 4-3 provides a summary of the model development, cost parameters as well as the MIP mathematical model; Section 4-4 illustrates the results under several demand scenarios, weighted distance and relative cost of CIM to OTS products; Section 4-5 contains the discussion, conclusion and potential future work.

4-2. Literature Review

A review on facility location and supply chain management by (Melo, Nickel et al. 2009) indicates that facility location decisions play a crucial role in the strategic supply chain networks. They identified the substantial characteristics of a facility location model to address the supply chain management (SCM) needs. The base models presented in the literature more than a decade ago are multiple allocation and the single allocation uncapacitated hub location problems, with and without a constraint on the number of hubs (Contreras, Fernández et al. 2007). The formulation for the multiple allocation case was provided by (Campbell 1994). Later, (Klincewicz 1991, Klincewicz 1996, O'Kelly, Bryan et al. 1996, Skorin-Kapov, Skorin-Kapov et al. 1996, Ernst and Krishnamoorthy 1998, Ernst and Krishnamoorthy 1999, Mayer and Wagner 2002) studied several improvements with the main objective of reducing the number of variables. In a typical Hub
Location Problems (HLP), the locations of hub nodes and the allocation of non-hub nodes to located hubs (for sending the commodities) have to be determined. Several variant of HLPs have been developed analogous to well-known discrete facility location problems, such as hub median, hub center and hub covering location problems (Mohammadi, Torabi et al. 2014). On the other hand, as hub locations are restricted to the nodes of the network, the problem is a vertex location problem (Owen and Daskin 1998). The single allocation case has been studied by (Klincewicz 1991, Aykin 1995, Klincewicz 1996, O'Kelly, Bryan et al. 1996, Skorin-Kapov, Skorin-Kapov et al. 1996, Ernst and Krishnamoorthy 1999). The capacitated single allocation problem has also been studied by (Ernst and Krishnamoorthy 1999, Labbé, Yaman et al. 2005).

(Meier, Clausen et al. 2016) developed a compact linearization of Euclidean distance with the aim of minimizing overall transportation cost for a single hub allocation problem. If all the requests of a customer (in our case a hospital without AM center) assigned to the same hub, that model would be a single hub allocation model. (Ghodratnama, Tavakkoli-Moghaddam et al. 2015, Abyazi-Sani and Ghanbari 2016) solved an uncapacitated single hub allocation by using tabu search (TS). They found the initial solutions and then considered the possible moves of locations and allocations. They construct a feasible allocation for each location move. (Sender and Clausen 2013) considered multiple hub nodes and used heuristic methods to solve a capacitated multiple hub allocation model for German Wagonload traffic. A combined transshipment methods to design a service network and hub location problem has been taken into account by (Rothenbächer, Drexl et al. 2016). For more accuracy Rothenbächer et al. determined the number of required means of transport to provide the needed capacity for each link individually. In addition, they considered the option of direct transportation from origin to destination at higher costs which will be
investigated in our study. A metaheuristic TS method has been used for multiple hub location allocation problem to minimize the transportation costs, connectivity costs, and fixed location costs under service time requirements by (Ishfaq and Sox 2011). They claimed that the fixed cost plays a significant role in their hub network which the direct effect of that could be a reduction in number of hubs in the network. (Fazel Zarandi, Davari et al. 2012) address the multiple allocation hub covering problem considering backup coverage and mandatory dispersion of hubs to satisfy a demand within a time bound.

Another important extension is the inclusion of stochastic components in facility location models (Snyder 2006). This is motivated by the uncertainty that often can be associated with some of the parameters such as future customer demands and costs. (Owen and Daskin 1998) provide an overview of research on facility location which, through the consideration of time and uncertainty, has led to more realistic models. (Chakrabortty, Akhtar Hasin et al. 2015) used possibilistic environment particle swarm optimization (PE-PSO) for aggregate production plan (APP) with uncertain production planning parameters. A multi period multi product APP formulated as an integer linear programing model to minimize the inventory costs, production costs and manpower cost. A constrained programming approach for uncertain hub location problem has been used by (Gao and Qin 2016) to minimize the maximal travel time for time sensitive distribution systems. The p-median center location problem involves in the study to minimize the maximal routing travel time from origins to destinations between any origin-destination pair. (Ambrosino and Grazia Scutellà 2005) studied a complex distribution network design problem which includes facility location, warehousing, transportation and inventory decisions. Their supply chain network is grouped into five layers including plants, central depots,
regional depots, big clients and clients which among them they introduced the transit points. They
considered two different scenarios static and dynamic for the problem and formulated twice with
and without considering time horizon.

(Melo, Nickel et al. 2006) proposed a mathematical modeling framework for a dynamic
multi commodity capacitated facility location. They captured important elements of supply chain
planning problem such as relocation of existing facility, capacity transfer including capacity
expansion, reduction and transfer to new locations, integration of inventory and transportation,
supply decisions and the availability of capital for facility opening and relocation. They affirmed
that one of the decomposition techniques or metaheuristic methods would be promising to solve
these types of supply chain network problems. (Ghodratnama, Tavakkoli-Moghaddam et al. 2015)
developed a fuzzy goal programming optimization approach to solve a multi objective hub
allocation location problem. They developed three objective functions for multi objectives of their
model. The first function has been used to minimize the total costs including transportation,
installation, vehicle costs, opening and reopening costs. In the second objective function the
service and transportation time have been minimized and finally in the third objective function the
total greenhouse gas emitted by transportation and manufacturing facilities has been minimized.
Another fuzzy multi objective multi product aggregate production planning had been developed
by (Gholamian, Mahdavi et al. 2015) to minimize the transportation cost of raw materials,
manufacturing plants, distribution centers, and customers while minimizing the cost of production
by considering the available warehouse space, hours of using machine for manufacturing product,
investment volume and number of regular and overtime workforce, subcontracting and
backordering costs.
Discrete facility location problem, where the location of new facilities is restricted to a finite set of available candidates, assumes that all candidate sites are equivalent in terms of the setup cost for locating a new facility. In this case, the number of facilities to be established typically becomes an endogenous decision. This new setting is known in the literature as the uncapacitated facility location problem (UFLP). In such problem, each demand point is allocated to the open facility that minimizes the assignment cost. One of the extensions of the UFLP is the capacitated facility location problem (CFLP) in which exogenous values are considered for the maximum demand that can be supplied from each potential site (Sridharan 1995). The difference is the closest assignment property is not necessarily valid in this case.

In our study a single period, multi commodity, capacitated multiple location problem is considered. Availability of direct transportation from origin of manufacturing facilities to the demand hospitals or destinations is another characteristic of our model. Problem definition and methodology of the research are reviewed in the next sections.

4-3. Model development

In the present study, distributed additive manufacturing is investigated to fabricate knee and hip implants in the state of Massachusetts to meet the several levels of local demand by analyzing the feasibility of the supply chain network of distributed manufacturing. In this MIP model, additive manufacturing facilities are allowed to locate just within the hospitals which are capable of performing hip and knee replacements. Figure 4-1 illustrates the candidate hospital locations and demands of the hip and knee implants for each hospital in the state of Massachusetts.
The proposed model can be considered as a hub-arc location model where the connectivity of the links between hubs is not required. The problem we addressed involves location, design, and routing decisions. The location decisions contain the location of the hubs (AM centers onsite of hospitals) on the nodes of the network. The design decisions include the routes the demand nodes are connected to the selected hubs. The routing decisions refer to track the flows between vertices of the network and the hubs. There is a unit transportation cost associated with each route according to the FedEx zone prices (FedEx 2019). The model determines the optimal number of AM facilities by minimizing the initial investment for opening additive manufacturing facility (hospital with manufacturing center), cost of transportation, cost of lead time, and distance in the network among AM facilities (hospitals with manufacturing center-hubs) and customers (hospitals without manufacturing center-demand nodes), while maximizing the coverage in the network. Several demand scenarios for CIM implants (5%-95%), relative production cost of CIM to OTS implants (1, 1.25, 1.5, 1.75, 2), and different penalty weights for pairwise distance (low, medium, high) among the facilities are explored where the outcomes are presented in the results section.
4-3.1 Model description and the cost parameters

Any of the nodes (hospitals which perform hip and knee replacements) can be chosen to be established an AM center (hub). Nodes which are not a hub cannot be used to manufacture and transport products. In this study, every demand node which is not a hub is assigned (allocated) to a single hub, so that all the flow to the demand node must be fulfilled from its hub. The hubs must always fulfill their own demands as well. A similar family of problems in the literature is the uncapacitated hub location family, in which the number of hubs is not predetermined but each node has an associated set-up cost. However, in this study, our model includes multi commodity and capacitated hub locations. We assume that the set-up costs for the hubs are similar at each potential location and it depends on the equipment in that location. One transportation mode will
be considered since the study is within the state of Massachusetts. The cost parameters used in the MIP model are presented in Table 4-1.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Unit</th>
<th>Resource</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital Cost for 3D Printers</td>
<td>Small: 200,000</td>
<td>$/ Unit</td>
<td>(ANIWAA 2019)</td>
</tr>
<tr>
<td></td>
<td>Medium: 450,000</td>
<td>$/ Unit</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Large: 700,000</td>
<td>$/ Unit</td>
<td></td>
</tr>
<tr>
<td>Transportation Cost</td>
<td>Out of state Hip: 200</td>
<td>$/ Unit</td>
<td>(FedEx 2019)</td>
</tr>
<tr>
<td></td>
<td>In state Hip: 150</td>
<td>$/ Unit</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Knee: 150</td>
<td>$/ Unit</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Knee: 110</td>
<td>$/ Unit</td>
<td></td>
</tr>
<tr>
<td>Product Cost</td>
<td>Hip: 2300</td>
<td></td>
<td>(Emelogu, Marufuzzaman et al. 2016)</td>
</tr>
<tr>
<td></td>
<td>Knee: 1900</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lead Time</td>
<td>60</td>
<td>Days</td>
<td>(Emelogu, Marufuzzaman et al. 2016)</td>
</tr>
<tr>
<td>Lead Time Cost</td>
<td>50 %</td>
<td>Of implant price</td>
<td>(Emelogu, Marufuzzaman et al. 2016)</td>
</tr>
<tr>
<td>Massachusetts Hospitals Data &amp; Locations</td>
<td>Hip: 14043</td>
<td>Implant / yr</td>
<td>(CHIA 2018)</td>
</tr>
<tr>
<td></td>
<td>Knee: 17998</td>
<td>Implant / yr</td>
<td></td>
</tr>
</tbody>
</table>

4-3.2 Mathematical model

In this section, facility location allocation model is formulated as an MIP model with the objective for minimizing the cost of capital investment, production, transportation, lead time and weighted distance. The inputs include the opening cost of AM facility with different types of equipment and capacity, production cost and production rate of each equipment, transportation cost per unit, and weighted distance to meet the required demand of customized hip and knee
implants for all the hospitals in Massachusetts that perform the replacement procedures. The model determines the optimal solution for production quantities for conventional/OTS and CIM implants and allocation of the hospitals to AM centers.

The following assumptions are used in developing the model:

1. The model is required to determine the optimal solution under demand uncertainty for CIM implants. Demand assumptions are taken into account according to the information in literature (Gregg 2014, Inc. 2016), where the expected demand for CIM implants increases in the future. In this study, the demand for CIM implants is assumed to be 5%-95% of the entire market demand.

2. Available time for production is assumed based on two work shifts per day, 7 days a week and 50 weeks a year. In total 5600 hours are available for production per year for each equipment/3D printer.

3. Each facility is capable of producing either hip or knee or both products. The capacity of each machine and consequently AM centers are limited according to the working hours and the production rate of each machine based on their print speed.

4. Inventory cost of conventional/OTS implants in the hospitals are considered similar to the raw material inventory cost for CIM implants if a hospital is a hub. Therefore, it is assumed that those costs offset each other and are not considered in the model.

5. The capital cost items include the equipment cost, ventilation system for the equipment and installation cost.
6. The production cost includes material, labor, energy consumption, pre and post processing costs.

7. The suppliers of the conventional implants assumed to be located out of state (outside of MA), since most of the demands of hospitals in Massachusetts are met by suppliers who are located in the Midwest region (MI and IN).

Based on these assumptions, the optimization model is developed with the following formulation. The sets and parameters of the MIP model are presented below:

**Sets:**
- \( P \) Set of products.
- \( N \) Set of hospitals performing knee or hip replacements.
- \( M \) Set of equipment/3D printers

**Parameters, constants, and coefficients:**
- \( Cam_{pmij} \) The capacity of an AM center for each product by considering the type of equipment being used in that center. \( p \in P, m \in M, i, j \in N, i \neq j \)
- \( Ctm_p \) The capacity of conventional manufacturing for each product. \( p \in P \)
- \( FC_m \) Fixed cost of the equipment type. \( m \in M \)
- \( TCam_p \) Transportation cost for in-state shipments of CIM products. \( p \in P \)
- \( TCtm_p \) Transportation cost for out-of-state shipments of conventional products. \( p \in P \)
- \( PCam_p \) Production cost of CIM products. \( p \in P \)
- \( PCtm_p \) Production cost of conventional products. \( p \in P \)
- \( Tam_p \) Lead time of CIM products. \( p \in P \)
- \( Ttm_p \) Lead time of conventional products. \( p \in P \)
- \( D_{pi} \) Demand of product \( p \) at location \( i \). \( p \in P, i \in N \)
- \( d_{ij} \) Pairwise distance between hospitals. \( i, j \in N \)
- \( \delta_p \) Lead time value for product. \( p \in P \)
- \( t_p \) Time to fabricate a product. \( p \in P \)
- \( \alpha \) Demand scenarios, percentage of the demand should be met by CIM implants.
- \( \lambda \) Relative production cost of CIM to conventional/OTS implants
- \( w \) Penalty weight to be used for distance minimization.
- \( T \) Available time for production, two shifts per day, 7 days a week, 50 weeks a year.
Decision Variables:

\( Q_{am_{pij}} \)  
Production volume of CIM products served to node \( j \) from hub \( i \). \( p \in P, i, j \in N \)

\( Q_{tm_{pj}} \)  
Production volume of conventional products served to node \( j \). \( p \in P, j \in N \)

\( x_{ij} \)  
Binary variable indicating if there is a hub at location \( i \) which serves location \( j \)

\( i, j \in N \)

The objective is to minimize the total costs including the production, transportation and lead time cost of the both CIM and OTS implants as well as the weighted distance among the conventional implant supplier, AM centers, and demand node hospitals. Thus, the objective function is calculated as the sum of the fixed cost of establishing an AM center onsite of hospitals, sum of the production, lead time and transportation costs, and sum of the weighted pairwise distance in the network. The pairwise distance is calculated based on Haversine formula which provides the minimum distance between two points on spherical shape by using latitude and longitude of each location (Chopde and Nichat 2013).

\[
\begin{align*}
\min & \sum_{m} \sum_{i}^{M} \sum_{j}^{N} FC_{m} * x_{ii} + \sum_{p}^{P} \sum_{i}^{N} \sum_{j}^{N} ((PC_{am_{p}} + \delta_{p} * T_{am_{p}}) * Q_{am_{pij}}) \\
& + \sum_{i}^{N} \sum_{j}^{N} w * d_{ij} + \\
& \sum_{p}^{P} \sum_{j}^{N} ((PC_{tm_{p}} + T_{cm_{p}} + \delta_{p} * T_{tm_{p}}) * Q_{tm_{pj}}) + \sum_{p}^{P} \sum_{m}^{M} \sum_{l}^{N} \sum_{j}^{N} TCam_{pmlj} * Q_{am_{pij}}
\end{align*}
\]

\( x_{ij} = 1 \) \hspace{1cm} \forall i, j \in N \hspace{1cm} (4-2)

\( x_{ij} \leq x_{ii} \) \hspace{1cm} \forall i, j \in N \hspace{1cm} (4-3)
\[ \sum_{j} Q_{am_{pij}} \leq C_{am_{pm}} \times x_{ii} \quad \forall i, j \in N, \forall p \in P, \forall m \in M \]  

(4-4)

\[ \sum_{j} Q_{tm_{pj}} \leq C_{tm_{p}} \quad \forall j \in N, \forall p \in P \]  

(4-5)

\[ \sum_{j} Q_{am_{pij}} \geq \alpha \times D_{pj} \times x_{ij} \quad \forall i, j \in N, \forall p \in P \]  

(4-6)

\[ \sum_{j} Q_{tm_{pj}} \geq (1 - \alpha) \times D_{pj} \quad \forall j \in N, \forall p \in P \]  

(4-7)

\[ \sum_{i} Q_{am_{pij}} \geq D_{pj} - Q_{tm_{pj}} \quad \forall i, j \in N, \forall p \in P \]  

(4-8)

\[ \sum_{p} \sum_{j} Q_{am_{pij}} \times t_{p} \times x_{ii} \leq T \quad \forall i, j \in N, \forall p \in P \]  

(4-9)

\[ Q_{tm_{pj}} \geq 0 \quad \forall j \in N, \forall p \in P \]  

(4-10)

\[ Q_{am_{pij}} \geq 0 \quad \forall i, j \in N, \forall p \in P \]  

(4-11)

\[ x_{ij} \in \{0,1\} \quad \forall i, j \in N \]  

(4-12)

Constraints (4-2) and (4-3) impose the maximum number of hubs that each demand node can be connected to, while ensuring that the point of connection is an established hub (AM center). Constraints (4-4) and (4-5) ensure that the production quantity of the CIM and conventional implants are less than the capacity of the production plants. Different demand scenarios for CIM (5%-95%) and conventional implants confirm via constraints (4-6) and (4-7). Constraint (4-8) ensures that the entire demand must be covered by using both CIM and conventional implants.
Constraint (4-9) assures that the production time of an AM centers remains lower than the available time for fabrication (2 shifts per day). Constraints (4-10) and (4-11) impose the non-negativity for the production quantity of CIM and conventional implants. Constraint (4-12) is the binary constraint for the decision variable of the model.

4-4. Results

One of the key parameters for determining the number and locations of the AM centers is relative production cost of CIM to conventional/OTS implants (λ). The relative production cost shows how expensive the CIM implants are in comparison with the OTS implants. Recognizing the minimal λ value that makes CIM implants economically feasible is very important. Therefore, testing different values of λ as an input to the MIP model could provide insightful recommendations for decision makers. Figure 4-2 illustrates the relationship of the relative production cost of CIM to conventional/OTS implants and the numbers of the AM centers opened for different priority levels of the weighted distance at low, medium and high. As presented in the Figure 4-2, when the CIM implants are 1.75x or more expensive than their competitors, regardless of the priority level assigned to the distance, the model would decide not to establish an AM facility for implant fabrication due to the high production cost of the CIM implants; since, the other cost benefits of the CIM implants cannot offset the higher cost of production. Therefore, all the demands would be met by the conventional implants. Lower λ leads to establishing more AM centers regardless of distance priorities. 6 AM centers are recommended to be opened when low priority is assigned to the distance in the network while, the relative production cost of CIM to conventional implants is one.
As shown in Figure 4-2, when the medium or high priority is assigned to the weighted distance, the highest number of recommended AM centers to be opened is 5 and 3 respectively.

Further investigation is performed to explore the optimal percentage of CIM demand coverage by considering different levels of relative production cost and weighted distance. More detail on the demand coverage, number of AM centers, weighted distance priority, and relative production cost ratios are presented in Table 4-2. When low priority is assigned to the distance, from 0% to 100% of the demand can be met by CIM implants based on different relative production cost of CIM to conventional. 100% of the demand can be fulfilled by 6 AM centers for low priority distance. When medium priority is assigned to the distance, yet again, from 0% to 100% of the entire demand can be covered by CIM implants depending on the relative production cost ratio. In this scenario, 100% of the demand can be fulfilled by 5 AM centers. Finally, when
high priority is assigned to the distance, from 0% to 19% of the demand can be covered by CIM implants considering the relative production cost ratio. These results indicate that under high distance priority, it wouldn’t be optimal to cover more than 19% of the demand from CIM products since the model minimize the total distance in the network as a top priority. In this case, 19% of the demand can be met by 3 AM centers.

Table 4-2: CIM optimal demand coverage percentage and AM centers under different distance priorities and production cost ratios

<table>
<thead>
<tr>
<th>Distance Priorities</th>
<th>Production cost ratio (AM to TM)</th>
<th>Number of AM centers</th>
<th>Demand coverage by CIM products (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>1</td>
<td>6</td>
<td>100</td>
</tr>
<tr>
<td>Low</td>
<td>1.25</td>
<td>5</td>
<td>97</td>
</tr>
<tr>
<td>Low</td>
<td>1.5</td>
<td>5</td>
<td>96</td>
</tr>
<tr>
<td>Low</td>
<td>1.75</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>Low</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Medium</td>
<td>1</td>
<td>5</td>
<td>100</td>
</tr>
<tr>
<td>Medium</td>
<td>1.25</td>
<td>5</td>
<td>97</td>
</tr>
<tr>
<td>Medium</td>
<td>1.5</td>
<td>3</td>
<td>19</td>
</tr>
<tr>
<td>Medium</td>
<td>1.75</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>Medium</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>High</td>
<td>1</td>
<td>3</td>
<td>19</td>
</tr>
<tr>
<td>High</td>
<td>1.25</td>
<td>3</td>
<td>19</td>
</tr>
<tr>
<td>High</td>
<td>1.5</td>
<td>3</td>
<td>19</td>
</tr>
<tr>
<td>High</td>
<td>1.75</td>
<td>2</td>
<td>2.5</td>
</tr>
<tr>
<td>High</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

In addition, further investigation is performed to assess the CIM products under three levels of demand scenarios and weighted distance, by considering the relative production cost of CIM as twice the conventional/OTS implants. As shown in the previous section, when the production cost ratio ($\lambda$) equals to 1.75x, the model recommends using conventional implants to minimize the total cost; however, in this section, we fixed the ($\lambda$) ratio to two, then imposed three levels of CIM demand coverage at 5%, 40% and 75% to explore how the model reacts to those changes under low, medium and high distance priorities. Not surprisingly, when higher demand is enforced to be
met by the CIM implants, the model recommends opening more AM centers regardless of distance priorities. The results for the low and medium distance priorities among the hospitals in the network are similar. Figure 4-3 presents the number and locations of the AM centers when 5% of the entire demand to be met by the CIM implants. As illustrated in Figure 4-3, three AM centers at the high demand hospitals (New England Baptist, Brigham and Women and MGH) would be enough to meet the 5% of the demand. The figure also shows which hospitals are covered by which of the three AM centers in this scenario. When high priority is assigned to the distance factor in the MIP model, it would recommend opening 52 AM facilities out of 55 candidate locations to minimize the total cost. Under this scenario, it’s not recommended to open an AM center onsite of low demand hospitals including Neshoba valley, Baystate Mary Lane, and Martha’s Vineyard hospitals as shown in Figure 4-3. All the other hospitals except New England Baptist which covers the demand of the three mentioned hospitals, just cover their own demands.

CIM demand: 5% of total demand
Distance priority: Low, Medium
Number of AM centers: 3
Location of AM centers onsite of hospitals:
1) New England Baptist
2) Brigham and Women
3) Mass General Hospital

5% CIM coverage with low and medium priorities for weighted distance
Figure 4-4 shows the number and locations of the AM centers when 40% of the entire demand must be met by the CIM implants. As shown in Figure 4-4, 6 AM centers at the high demand hospitals (New England Baptist, Brigham and Women, MGH, South Coast, Lahey, and Newton Wellesley) is adequate to meet the 40% of the demand. By assigning high priority to the distance factor in the MIP model, similar to the 5% demand scenario, this time, the model would recommend establishing 53 AM facilities out of 55 candidate locations. Under this scenario, it’s not recommended to open an AM center onsite of Baystate Franklin and Baystate Mary Lane hospitals as shown in Figure 4-4. Again, all the other hospitals except New England Baptist which covers the demand of Baystate Franklin and Baystate Mary Lane hospitals, cover their own demands. Additionally, Figure 4-5 presents the results of the AM centers locations under the 75% CIM demand scenario. 6 AM centers would be enough to meet the 75% demand under low and
medium distance priorities at the same locations as the 40% demand scenario. Under the high distance priority, 52 AM centers to be established while, New England Baptist and Baystate Mary Lane cover the demand of the three remaining hospitals as shown in Figure 4-5.

**CIM demand: 40% of total demand**
**Distance priority: Low, Medium**
**Number of AM centers: 6**
**Location of AM centers onsite of hospitals:**
1) New England Baptist
2) Brigham and Women
3) MGH; 4) South Coast; 5) Lahey
6) Newton Wellesley

40% CIM coverage with low and medium priorities for weighted distance
CIM demand: 40% of total demand
Distance priority: High
Number of AM centers: 53
Location of AM centers onsite of hospitals:
All the hospitals performing knee and hip replacement BUT
1) Baystate Franklin; 2) Baystate Mary Lane

40% CIM coverage with high priority for weighted distance

Figure 4-4: Effects of 40% CIM demand scenarios and weighted distance on the number and locations of AM centers

CIM demand: 75% of total demand
Distance priority: Low and Medium
Number of AM centers: 6
Location of AM centers onsite of hospitals:
1) New England Baptist
2) Brigham and Women
3) MGH; 4) South Coast; 5) Lahey
6) Newton Wellesley

75% CIM coverage with low and medium priorities for weighted distance
Figure 4-6 a and b illustrate the relationship among CIM relative production cost ratio to conventional/OTS implants (\(\lambda\)), as an independent variable, percentage of demand coverage, as an independent variable, and total cost (objective function value), as a response variable, when the distance priority sets to low. The contour plot, Figure 4-6 a, indicates that the higher costs can be incurred when a higher rate (\(\lambda\)) is used for the relative CIM production to OTS; however, it depends on the magnitude of the (\(\lambda\)). As illustrated in Figure 4-6 a, when (\(\lambda\)) is less than 1.75, surprisingly, covering higher demand with CIM products can be less expensive. While (\(\lambda\)) is greater than 1.75, covering more demand by CIM implants would be more expensive in this case. If we focus on Figure 4-6 a, it is obvious that the lines which present (\(\lambda\)) smaller than 1.75 follow the similar trend while their trend is different than the lines represent (\(\lambda\)) greater than 1.75.
In addition, Figure 4-6 b also can support the discussed results in Figure 4-6 a. As illustrated in Figure 4-6 b, the total cost increases slightly as the CIM demand coverage increases when the relative production cost ratio ($\lambda$) is higher than 1.75. In this case, when the model is enforced to meet the higher demand by CIM products, the high CIM production cost cannot be offset by the lead time and distance penalties in the model; therefore, a slight increase in the total cost can be justified. On the other hand, when the relative production cost ratio ($\lambda$) is less than 1.75, the total cost would be decreased when higher proportion of the demand met by CIM implants which means the higher production cost of CIM implants can be easily offset by the lead time and distance penalties. In this case, as shown in Figure 4-6 b, the total cost decreases as CIM products cover more demand in such a way that the least cost on the surface plot belongs to $\lambda = 1$ and 85% CIM demand.

**Contour plot of the relationship between CIM relative production cost ratio to conventional implants and CIM demand coverage as independent variables and total cost as response variable**

a) Contour plot of the relationship between CIM relative production cost ratio to conventional implants and CIM demand coverage as independent variables and total cost as response variable
b) Surface plot of the relationship between CIM relative production cost ratio to conventional implants and Figure 4-6: Effects of the CIM relative production cost ratio to conventional implants and portion of the CIM demand coverage on total cost while distance priority set to low.

4-5. Discussion and Conclusion

The decision tradeoffs for fabricating CIM implants onsite of hospitals in the state of Massachusetts were considered for investigation. The goal of the study is to explore the decision tradeoffs in optimal level for locations and capacities of AM centers, the volume of each product type (conventional and CIM hip and knee implants), distance in the supply chain network, transportation and lead time costs. The MIP model presented in section 4-3 of this study was used to investigate the mentioned goals and recognize the cost elements which have significant impacts on the higher adoption of CIM implants. One of the benefits of the model is that it allows decision
makers to assign fixed values for some of the objectives in the MIP model and explore values for the other objectives based on their preferences.

The results demonstrate several demand scenarios for CIM implants (5%-95%), various relative production cost of CIM to conventional/OTS implants, and different penalty weights for pairwise distance among the hospitals performing knee and hip replacement procedures in the state of Massachusetts. Based on the relative production cost ($\lambda$) analysis, CIM implants would be economically feasible for use in Massachusetts when the relative production cost is less than 1.75x. Nonetheless, when the relative production cost is higher than 1.75x, to minimize the total cost, the model recommends that all the hospitals in the network order their required demands from conventional implants supplier. Our analysis also recommended that if the relative production cost of CIM to conventional implants is less than or equal 1.75x, fulfilling higher proportion of the demand from CIM products would be more profitable.

To explore a range of alternative preferences for distance among the nodes (out of state conventional implants supplier, hospitals with and without AM centers) in the network, the model was run with various priorities for the distance element. When a high priority is assigned to the distance, to minimize the total cost, the model recommends establishing an AM facility with lower capacity (at most 2 3D printers in each AM center) in more than 94% of the hospitals. On the other hand, when low or medium priority is assigned to the distance element, the model recommends establishing AM center with higher capacity (up to 6 3D printers) in 5 or 6 different hospitals to meet the required demands of CIM products. The results illustrate that if the distance is assigned high priority, it would be more beneficial to open more AM facilities.
This research can be further expanded to consider more cost factors. The initial investments for the 3D printers capable of fabricating metal products can be considered for sensitivity analysis when more information is available on price forecasting of such 3D printers. In this study, we used the current level of capital investment for the required equipment. To perform such analysis, the trend in the cost of 3D printers in the past decades can also be used; however, for more meaningful analysis, it would be helpful to just consider the price trend of the machines that are capable of manufacturing precise metal products such as SLM 3D printers. Another factor to consider for further analysis is the lead time cost penalty which shows the urgency of a product. A challenge to assess the lead time cost is the uncertain nature of this factor when it comes to the value of delay in hip and knee procedures which varies on case by case basis. In some cases, the procedure can be delayed without any severe impact on the patients while, in other cases, that delay might have an extreme impact on QOL of the patients. Finally, the probability for different demand scenarios can be defined based on the CIM demand expectations in the future to make the model stochastic. The focus of this study is on utilization of the CIM implants through establishing AM centers onsite of hospitals in the state of Massachusetts. However, the proposed model can be used for larger network, such as the northeast region or the entire US. The model also can be expanded to consider other types of the customized products.
Chapter 5
Conclusions

Governments all around the world consider energy security as a serious societal objective which includes domestic energy production, energy independence, energy access, and etc. (Iyer, Calvin et al. 2018). Solar energy is expected to be one of the largest contributors to energy security and renewable energy mix by 2040 because of falling cost factors, improvement in efficiency and flexibility of installation (IEA 2017, Dholakia 2018). The growing demand for decentralized manufacturing and mass customization (Mourtzis and Doukas 2013, Matt, Rauch et al. 2015, Eggert, Jetli et al. 2017) would result in smaller facilities that could realistically rely on onsite generation of energy through renewable resources. This manufacturing transition could reduce energy consumption for production and transportation, and would contribute to more sustainable environment and society (Mourtzis and Doukas 2013, IPCC 2015).
According to (De Weck, Reed et al. 2014), advanced manufacturing is the integrated solution for production of physical products with the goal of improving customization, process efficiency and recycling procedures. Advanced manufacturing can be considered as a bridge to connect smart and digital manufacturing. As discussed in this dissertation, smart manufacturing has four key trends: 3D printing/additive manufacturing, distributed manufacturing, demand driven supply chain and Internet of Things driven analytics. Additive manufacturing as one of the subgroups of smart manufacturing refers to the processes that digital 3D design data is used to fabricate the final product in layers by depositing materials. Additive manufacturing can provide less energy and materials use, faster cycle time, distributed and decentralized manufacturing, customized products, and manufacture complex geometries. Since, additive manufacturing can provide mass customization with faster cycle time, these processes can revolutionize healthcare and are becoming popular in this area.

In this dissertation, various policies with the focus on improving sustainability in manufacturing by adopting emerging technologies for onsite energy generation and customized product fabrication to improve healthcare economic and patient quality of care are explored.

Chapter 2 targets the industrial sector as one of the top energy consumers and GHG emitter in the U.S. to provide a systematic framework to reduce fossil fuel based energy consumption and emissions to improve economic and environmental pillars of sustainability in manufacturing. An energy simulation tool (SAM), developed by NREL, along with the manufacturing energy consumption survey data, gathered by EPA, are utilized in this chapter to provide meaningful insights to policy makers and manufacturers in regards to the economic and environmental
potentials in different states by adopting high efficiency roof-mounted solar PVs as an alternative source for electricity generation onsite of the manufacturing facilities. The findings illustrate that around 70% of the industries could consider solar PVs for their required energy production during spring and summer time in the states such as Arizona, California, Colorado, Hawaii, Idaho, Minnesota, Nevada, New Mexico, Texas, and Wyoming. Additionally, the economic and environmental outcomes are investigated in the five states case study in chapter 2. This analysis explores different financial incentive and regulation scenarios for industrial sector to distinguish effective renewable energy policies. Effective regulatory policies such as permits, net metering, interconnection, RPS, FiT and financial incentives such as production-based incentives, and tax credit could directly or indirectly support the prevalent adoption of high efficiency roof-mounted PV systems by manufacturing facilities. The results illustrate that the adoption of high efficiency solar PVs by the industrial sector can provide environmental and economic advantageous for manufacturing facilities in 25 years study period.

Ascending healthcare costs is a growing concern for the healthcare industry and patients in the United States. Healthcare expenditures in the U.S. grew to $10,739 per person in 2017 which accounted for 17.9% of GDP, more than any other developed countries (CMS 2018). This and other reports (Baicker and Chandra 2004, Baicker and Goldman 2011, Baicker, Chandra et al. 2012) highlight the need for healthcare strategies reform to achieve more effective long-term policies to decrease costs and improve quality of care. Considering a flat rate of insurance companies’ reimbursement for any episode of care, which place significant financial pressure on service providers and potentially patients, a systematic prospect is required to achieve long-term effective strategies. Two of the most common procedures in the U.S. with a high rate of
dissatisfaction among the patients, while experiencing an exponential increase in the number of patients in the past decade, are hip and knee joint replacement procedures. Therefore, in chapter 3, an integrated framework is developed to perform what-if analysis (not how to improve) for hip and knee joints replacement procedures in the U.S. to improve quality of care with potentials to reduce healthcare costs in the long run which lead to societal and economic improvement of sustainability pillars.

Chapter 3 targets the hip and knee implant fabrication procedures to provide a systematic framework to improve patient wellbeing and reduce healthcare costs which lead to improve the social and economic pillars of sustainability in manufacturing. A system dynamics model is developed to provide meaningful insights for policy makers regarding the insurance reimbursement coverage for CIM implants which leads to higher adoption of these products. In the system dynamics model, the adoption rate of CIM implants is dependent on surgeons’ recommendations and out-of-pocket surgery cost for patients, which is highly reliant on the levels of coverage of insurance bundled payment programs for CIM procedures. Higher adoption rate of CIM implants could improve some categories of patient outcomes while reducing the healthcare costs including hospitals costs, insurance providers cost, and patients out-of-pocket expenditures. Other metrics considered in this chapter including 90-day readmissions, 3-year revision surgery rates, procedure times, and recovery time after primary knee replacements can be improved by higher adoption of CIM hip and knee implants. All the economic and social metrics are investigated under several scenarios for insurance coverage levels of CIM implants. The findings illustrate that the same level insurance coverage for CIM implants as the level of coverage for conventional implants, could lead to higher adoption of these products and consequently better
patient performance and satisfaction. The modeling approach and systems thinking in this chapter could be considered for the adoption of any emerging customized therapies for personalized medicine.

Distributed additive manufacturing have some advantages over conventional manufacturing such as reducing materials and energy consumption, simplifying production, redesigning supply chain network into decentralized network, etc. which can lead to more sustainable manufacturing. To address the effects of decentralized additive manufacturing in medical area, chapter 4 targets the hip and knee implants fabrication procedures through distributed additive manufacturing in a case study for the state of Massachusetts. A mixed integer programming (MIP) optimization model is developed to provide meaningful insights to decision makers regarding the adoption of distributed additive manufacturing for hip and knee implant fabrication onsite of hospitals in the state of Massachusetts to meet the growing demand of the CIM products. The production cost, transportation cost, lead time cost for product delivery and the weighted distance in the network are integrated in the MIP model which solved by Gurobi solver. The outcome of the model recognizes the cost factors which have a significant impact on the adoption of CIM implants. Additionally, the model could determine the optimal volume of each product type, locations of the AM centers, allocated hospitals to each AM center and conventional implants supplier, and the total cost under several demand scenarios, relative production costs, and various distance penalties. The modeling approach in this chapter could be considered for decision tradeoff assessment of CIM implant fabrication to improve personalized medicine and healthcare economics.
Through this dissertation, it is illustrated that to improve manufacturing sustainability by adoption of emerging technologies, the focus should be on adjustments of long-term strategies and policies. It is indicated that effective policies could improve consumer wellbeing and satisfaction, energy and material efficiency, and economic which can provide sustainable development. To that end, this dissertation can be considered as one step ahead to justify, adopt and switch to the new technologies in each angle of manufacturing from energy resources to the production lines and supply chain network.
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