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# General Electric Uses an Integrated Framework for Product Costing, Demand Forecasting, and Capacity Planning of New Photovoltaic Technology Products

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General Electric (GE) Energy's nascent solar business has revenues of over $100 million, expects those revenues to grow to over $1 billion in the next three years, and has plans to rapidly grow the business beyond this period. GE Global Research (GEGR), in partnership with GE Energy's solar platform team, is pursuing a number of technological alternatives to bring new low-cost solar products to the market. However, the GE solar business is facing a challenge—making optimal investment decisions to realize its growth objectives in the presence of major uncertainties in technology, costs, demands, and energy policy. We have developed analytical decision support tools with embedded mathematical models to estimate product costs and demands, and to support capacity planning decisions under cost and demand uncertainties. In this paper, we outline our algorithmic approach and system implementation, which help to support strategic decisions at GE.

*Key words*: facilities planning; cost analysis; capital budgeting; forecasting; risk; mathematical programming.

Governments around the world are aggressively promoting renewable sources of energy to combat global warming and decrease dependence on fossil fuels. The US Department of Energy's (DOE) solar energy technology program aims to make electricity generation from photovoltaic (PV) cells cost-competitive compared to electricity generation from conventional sources by 2015 (US Department of Energy 2009). Its strategy includes pursuing complementary activities on research and development (R&D) and using an integrated system-driven approach for value analysis. Its program goals are to reduce costs through R&D and to eliminate market barriers.

General Electric (GE) is a world leader in energy and a leading supplier of power generation and energy delivery technologies; its 2007 revenues were $21 billion (GE Energy 2009). GE Energy works in all areas of the energy industry: coal, oil, natural gas, and nuclear energy; renewable resources, such as water, wind, solar, and biogas; and other alternative fuels. GE Energy's nascent solar business has revenues of over $100 million, which are expected to grow to over $1 billion in the next three years (Malone 2008). Plans are underway to rapidly grow the business beyond this period.

GE Global Research (GEGR) is GE's central R&D organization. It employs over 2,500 researchers at four multidisciplinary facilities and delivers innovations and technological breakthroughs that drive growth for GE businesses and that revolutionize markets. GEGR and the GE solar platform team have received support from DOE's solar energy technology program to accelerate research on a solar energy program; their goal is to significantly decrease the cost of manufacturing and distributing solar electricity.

GE's solar platform covers various aspects of the PV value chain, including forming partnerships with installers to provide complete system installation for commercial and utility-scale (1 MW or larger) customers (see Figure 1). The solar industry is still in a development stage; without incentives and financing, the solar industry is currently not cost competitive with conventional energy industries, such as coal and natural gas. Companies are undertaking R&D to improve PV module efficiency, reduce PV system



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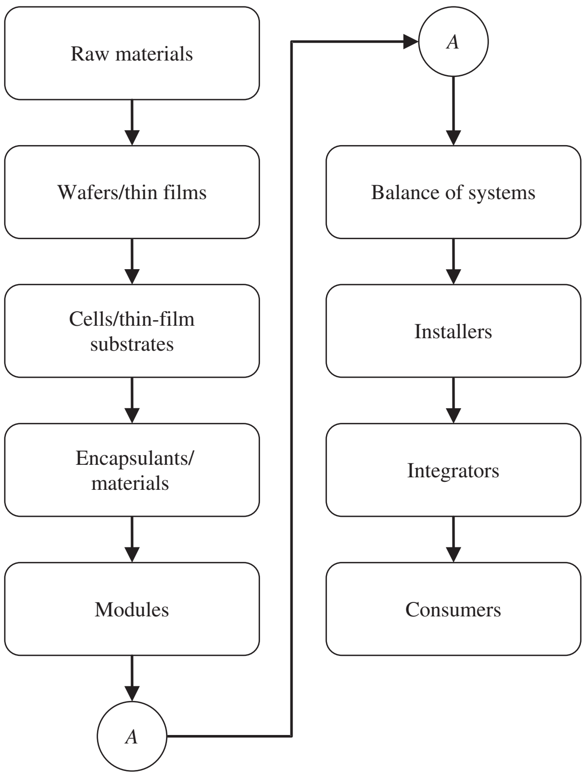


**Figure 1: We consider all the steps in the PV industry value chain to estimate the installation costs of PV systems.**

costs, and make strategic technology bets to gain market share.

GE is developing innovative technologies for the development of modules and balance of systems (BOS) required for complete installation. In a PV system, BOS comprises all the equipment except PV modules and mounting structures. These research efforts require significant amounts of investments in time and equipment. The capital investment for setting up an infrastructure for manufacturing PV products usually requires millions of dollars. After they have demonstrated reliable prototypes, companies must automate the manufacturing of these technologies and plan for high-volume manufacturing. This requires understanding and estimating costs, demand, and competition in the product's market. Estimating the costs, demand, and capacity in the complex operating environment for PV products, which includes a myriad of factors affecting the returns, is challenging. A key challenge facing the GE solar business is making optimal investment decisions to realize its growth objectives in the presence of major uncertainties in technology, costs, demands, and energy policy. It needed tools to tie its PV R&D efforts with its product costing, market forecasting, and capacity planning.

Traditional approaches to strategic planning can be dangerous (Courtney et al. 1999). A question facing executives in the solar industry is to decide whether to bet big, hedge, or wait and see. Some executives favor investments that allow their company to adapt quickly as markets evolve, but the costs of this flexibility could be high.

This wait-and-see strategy may not be conducive to business viability when competitors are quickly seizing opportunities. Risk-averse managers may hedge their bets by making smaller investments; however, they would be restricted by their capacity to meet market demand if a big growth opportunity emerged; for example, the solar industry has been growing at a rate of 37.9 percent compound annual growth rate (Hodge 2008). Working with the skewed data that technologists provide also presents significant challenges. Although many models adopt a relatively static view of solar development activities and the market, which is consistent with a deterministic view of the world, we use scenarios to incorporate the dynamics of uncertainty and then optimize over them.

The problem of determining the optimal capacity investment plan has hundreds of parameters, which can be altered to evaluate capacity, cost, demand, and competition scenarios for business planning and economic evaluation of PV technologies. We are aware of no other work in this area that integrates costs, demand, competition, and capacity scenarios for business planning and strategic investment decisions. Because costs and demands are probabilistic, the investment problem is a large-scale, multiperiod stochastic optimization problem, which we formulate as a multiscenario linear programming model. When the dimensions of the data vector are large and many scenarios are under consideration, the resulting model is computationally challenging. We approach the fundamental issue of trading off between level of detail and management ease of use by reducing the complexity of our approach and using methods that approximate the true solution. We developed the

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following analytical decision support tools and integrated them to help the business make better investment decisions.

*Product costing tool.* This tool estimates the cost of installing a unit of solar generation capacity while considering product technology and design, production process, install application type, and system component choices. We developed techniques to assign costs to processes and then to products based on the processes used in product manufacturing and system deployment. We use a standardized costing methodology and a common set of data assumptions, and we enable a unit-cost comparison of different PV technologies by resolving the scale dissimilarity issues.

*Market demand prediction tool.* Using the product cost estimates generated by the product costing tool, this tool predicts the solar demand by year, region, and market type across the United States over the next two decades. As input, the tool also needs data on the available rooftop space by region across the country, electricity rates, solar energy generation profiles, installed costs by technology, federal and state incentives, and government regulations. It builds on market penetration and technology adoption described in the marketing literature to predict the demand. We extend and use the methodology developed by Paidipati et al. (2008) in implementing this tool.

*Capacity planning tool.* Using the cost and demand estimates generated by the tools described previously, this tool enables decisions regarding production capacities for different PV technologies. It uses a scenario-based linear programming model that integrates cost and demand scenarios over a multiperiod planning horizon by considering competitive factors, budget constraints, and operations constraints for capacity planning.

Our objective is to provide a decision support system that will enable the business to plan for growth under various scenarios. Our approach—comparing multiple technologies by integrating product cost estimation, demand estimation, and capacity requirements—enables GE's solar platform team to make better business decisions. Using this elegant and easy-to-use decision support tool, the business can quickly evaluate any changes in R&D, manufacturing, the market, government policies, and competition by updating required data.

We have organized the rest of the paper as follows: We provide a review of literature in the areas of cost, demand, and capacity planning in the next section. The *Photovoltaic Technology* section gives a brief introduction to the different solar technologies that are relevant for our study. The following three sections titled *Product Costing*, *Demand Estimation*, and *Capacity Planning* outline the methodologies that we developed to estimate costs, demands, and capacity requirements, respectively. The *Implementation and Benefits* section briefly describes the software implementation of our algorithm and the benefits realized.

## Literature Review

A considerable amount of literature has been written on cost estimation, demand forecasting, and capacity planning. Much of a product's manufacturing cost is established through decisions made during the design stage (Whitney 1987). Several textbooks (e.g., Jelen and Black 1983) are available on this topic. Gruber (1996) categorizes estimation techniques into groups based on the techniques employed: detailed breakdown, simplified breakdown, group technology, regression, and activity. Jiao and Tseng (1999) describe a method for estimating product cost during the early design stages, prior to the actual production run, when much of the manufacturing cost is still to be determined. Their method is based on an activity-based costing approach and uses historical cost data on similar products. Abraham and Prasad (1969) assume that the unit manufacturing cost in the presence of random demands and yields is stochastic and develop methods to estimate 90 percent confidence intervals for the base manufacturing cost. Sun et al. (2007) describe a manufacturing cost-estimation method based on an activity-based costing method for an aeronautic part. Because we know that PV product costs will fall significantly over time, we must reliably account for these cost reductions. Traditional methodologies for forecasting such costs rely on learning-curve models. We have enhanced our cost models to include both learning curves and trends in technology development, material cost and usage, labor costs, and overhead reduction activities.

Urban et al. (1996) address the challenges of forecasting demand for new products. They describe how

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a major automobile manufacturer combined a new measurement methodology (i.e., information acceleration) with existing marketing research methods to forecast potential sales of a new electric vehicle. Janssen and Jager (2002) present a model-based analysis of the introduction of green products. They model both consumers and firms as populations of agents who differ in their behavioral characteristics. Maier (1998) shows the potential of using system dynamics as the modeling methodology in the field of new product diffusion models. Paidipati et al. (2008) develop a methodology to estimate solar demand across the United States; however, their technique does not consider financing availability, which is crucial in the solar industry in which most of a PV system's costs are incurred upfront.

Decisions by individual companies concerning the level of production capacity in watts are discussed in great detail in the press (Mitsubishi Electric 2004, US Department of Energy 2009). Ahmed et al. (2003) provide a multistage stochastic integer formulation model for multiperiod investment of capacity planning with uncertainty in demand and cost parameters. Eppen et al. (1989) describe a model developed to aid General Motors in capacity decision making for four of its auto lines; their model incorporates elements of scenario planning, integer programming, and risk analysis.

The algorithms for costing, demand forecasting, and capacity planning, as discussed in the literature, are developed in isolation and are not integrated. Most of the models are theoretical exercises and do not consider the realities of manufacturing, market dynamics, and the existing business. In our experience, most businesses do not use advanced mathematical models for strategic planning; they rely on simple Microsoft Excel tools. Consequently, demand analysis and capacity planning take months and are duplicated for each new technology introduced. Major opportunities exist for better decision making in new-technology introduction and commercialization.

## Photovoltaic Technology

A number of technologies can be used to harness solar energy (see Figure 2). These can be broadly classified into PV and concentrating solar power (CSP) systems. PVs, also known as solar cells, convert sunlight directly into electricity. CSP systems use a multitude of techniques to focus a large area of sunlight into a small beam. The concentrated light is then used as a heat source for a conventional power plant (concentrated solar thermal) or is concentrated onto PV surfaces (concentrated solar PVs). PV technologies can be used in residential and commercial rooftops, whereas CSP is used mainly in large-scale utility

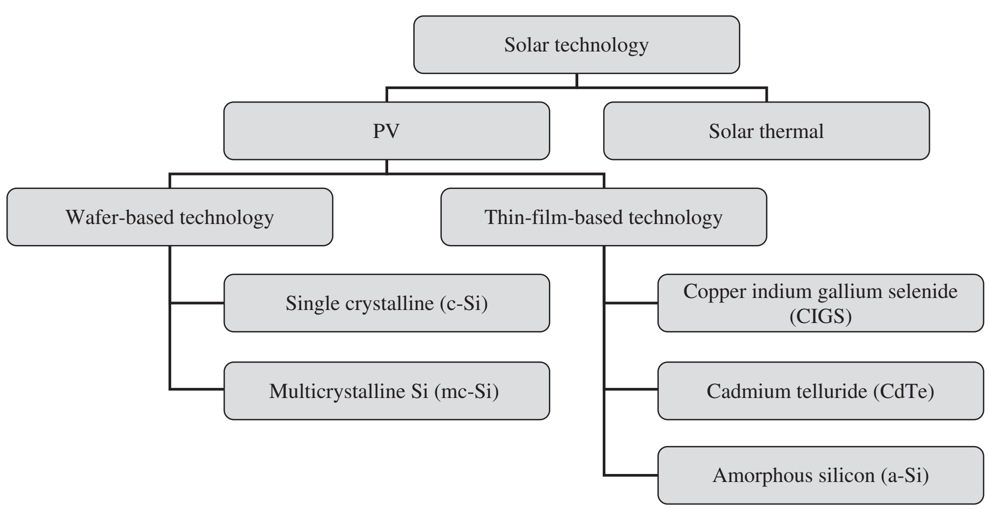


**Figure 2: A number of technologies are available for generating electricity from solar power.**

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applications. Although we focus on PV in this paper, our methodologies also apply to other technologies.

PV can be broadly classified as either wafer or thin film, based on the technology used. Based on the type of material used to make the cells, each class can be subdivided (see Figure 2). These technologies differ from one another based on their manufacturing methods required, production costs, and performance. The performance of a solar cell is measured in terms of its efficiency in converting solar energy into electricity.

*Wafer-based technology.* Crystalline silicon wafer-based cells are manufactured by slicing wafers from blocks of cast crystalline silicon. Polycrystalline silicon wafers are cheaper than monocrystalline silicon cells but have lower energy conversion efficiency. The energy conversion efficiency for these technologies ranges between 14 and 20 percent.

*Thin-film–based technology.* In a thin-film PV cell, a thin semiconductor layer of PV material is deposited on a low-cost, supporting layer of glass, metal, or plastic foil. Thin-film materials have higher light absorptivity than crystalline materials. The deposited layer of PV materials is extremely thin—from a few micrometers to even less than a micrometer. The deposition techniques, in which PV materials are sprayed directly onto glass or metal substrate, are cheaper. The manufacturing process is faster and uses less energy. Mass production is easier than the ingot-growth approach of wafer-based crystalline silicon technology. However, thin-film PV cells suffer from poor cell conversion efficiency because of their non-single crystal structure. We discuss some thin-film technologies below.

1. Cadmium telluride (CdTe) is a polycrystalline semiconductor compound made of cadmium and tellurium. CdTe has a high light-absorbing property that allows it to absorb 90 percent of the solar spectrum. It is relatively cheap to manufacture and has a conversion efficiency of approximately 7–11 percent.

2. Copper indium gallium selenide (CIGS) is a solid solution of copper indium selenide and copper gallium selenide. It also has the ability to absorb approximately 90 percent of the solar spectrum with a conversion efficiency of 10–11 percent. More than 10 companies are currently working on developing modules using CIGS-based technology.

3. Amorphous silicon (a-Si), a noncrystalline form of silicon, has light absorptivity that is approximately 40 times higher than that of crystalline silicon. a-Si can be deposited on various low-cost substrates, including steel, glass, and plastic, and it has module efficiencies in the range of 8–10 percent.

Crystalline silicon is currently the basic material used in most PV modules. Use of crystalline silicon for PV is prevalent, and the same technology used for chip manufacturing has been adapted for the PV industry. Extensive research has shown that crystalline silicon-based technologies can provide high efficiencies. However, despite the lower efficiencies of thin films, these technologies hold substantial cost-reduction potential. GE owns a crystalline silicon module manufacturing plant and has a majority stake in a CdTe thin-film production company (Sopelsa 2008).

As part of its solar technology portfolio, GE is investing in several PV technologies, including novel approaches that use low-cost solar-grade silicon, high-efficiency silicon-based systems, and nonsilicon thin-film technologies.

## Product Costing

The goal of our model is to estimate the total cost of an installed PV system; such costs vary based on the application (residential, commercial, or utility) and the size of the installation. We estimate the total installed cost by using a bottom-up modeling approach and by breaking down the cost components into direct materials, direct labor, and project overheads. A PV system also requires other components to convert, control, and distribute the energy produced by the system. The specific components required vary by design and application type; they include DC-DC converters, DC-AC inverters, module-mounting hardware, array combiners, surge protection and disconnect devices, wiring, grid tie meters, and other power-processing equipment. Before an installation project begins, the mechanical and electrical design for the PV system must be finalized. The mechanical design provides the detailed drawing that outlines the mounting equipment and installation plan consistent with the architectural and structural code requirements.

During the design phase, the layout, orientation, and configuration are selected for maximum

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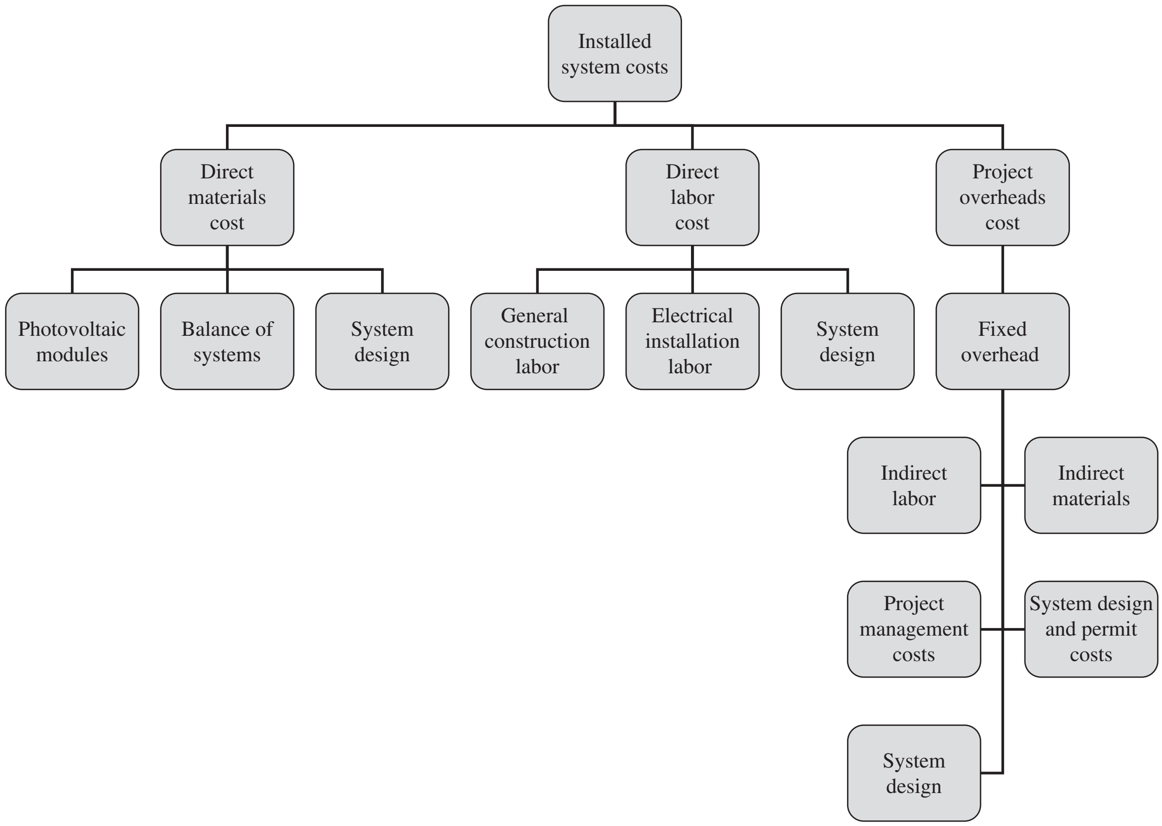


**Figure 3: A detailed breakdown of costs for a PV system installation helps in understanding the cost drivers.**

energy yield and minimum cost. The electrical design accounts for load requirements, design currents for all parts of the electrical circuit, sizing, and selection of the appropriate BOS components to meet National Electrical Code (NEC) requirements. A team of mechanical and electrical installers then installs the PV system under the supervision of project managers. Project management costs include site visits, site cleanup and setup, supervision, transportation, and material handling costs. The installation labor cost depends on the system size, components, and installer training and experience. The indirect materials are the tools and accessories required for the system's mechanical and electrical installation. Permit fees are generally required to cover the cost of the building inspectors, who ensure that the engineering and safety standards are met. Equation (A1) in Appendix A shows the total PV system installation costs for a system of a given size. The transfer functions in Equation (A1) are installation site-specific (e.g., solar radiation varies by geographic location). Although we have developed and implemented these transfer functions, their discussion is beyond the scope of this paper. Similarly, we model each of the installation components shown in Figure 3 in detail. However, in this section, we will only discuss the cost estimation for a PV module. The methodology for estimating other costs is similar.

PV modules, which are the central part of an installed PV system, represent a major part of total system costs. The unit cost of a PV module is influenced by module design, materials, manufacturing process, and plant size (see Figure 4). Our model requires detailed data on the following elements to accurately estimate PV module costs:

1. PV product design variables (module efficiency, voltage, current characteristics);

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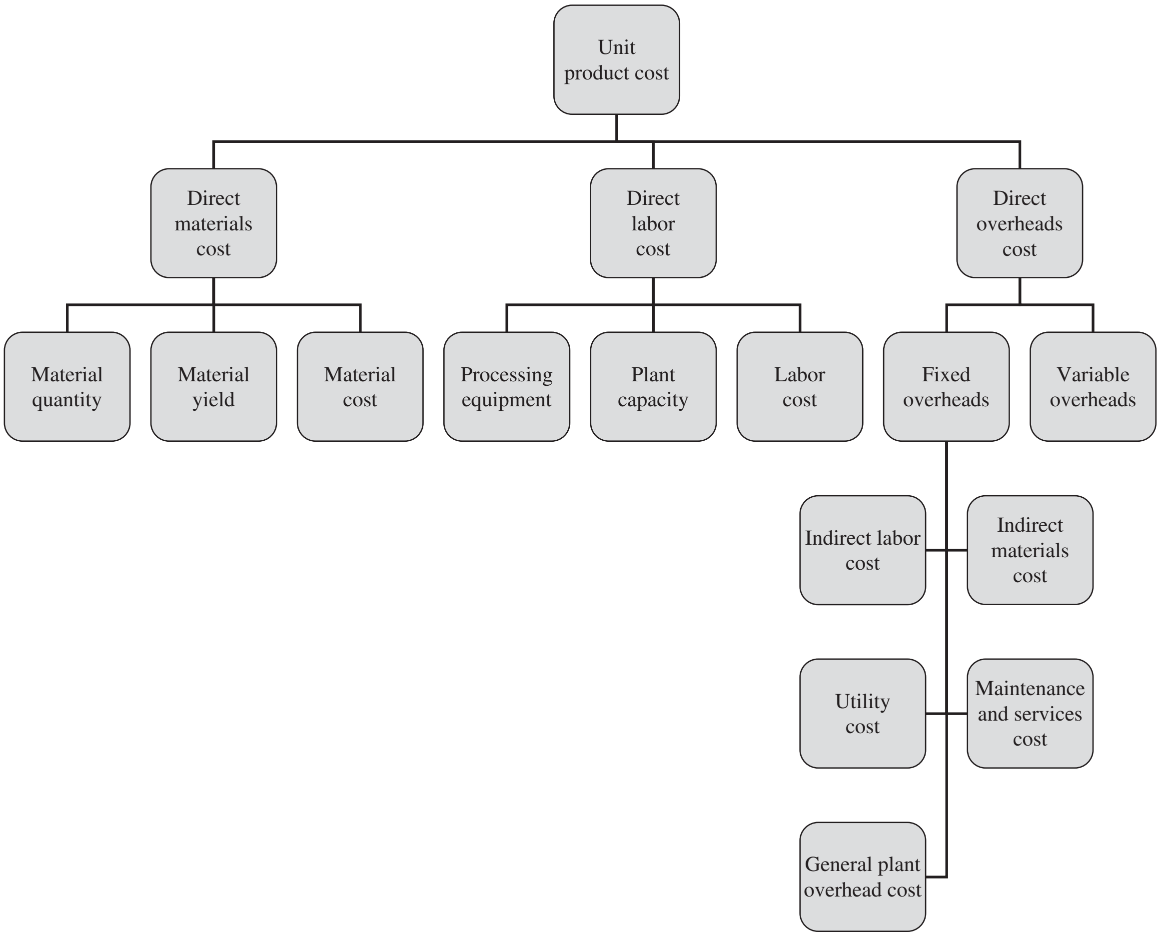


**Figure 4: We break down the PV module unit production costs into material, labor, and overhead costs. We model each cost at a significant level of detail.**

2. Manufacturing process definition and models (manufacturing and assembly steps with routing, manufacturing duration, production volume, process and material yield, equipment details, labor requirements);

3. Cost elements for each activity in the process (material cost, labor cost, equipment costs, expenditures, etc.).

We break down the PV module cost into direct material cost, direct labor cost, and direct overheads (see Figure 4). To estimate the material costs, we generate the bill of materials (BOM) depending on the module design specifications (see Appendix A). The BOM contains information about materials, components, or subassemblies, which go directly into the module or are used as consumables. We estimate and then aggregate item costs incurred at each manufacturing process to determine the total direct material costs, which, at each process, are driven by material yield, quantity used, and material cost (see Appendix A). The user specifies the BOM data items in detail. The items that comprise the BOM could be manufactured in-house or in a different facility that GE owns and operates, or it could be outsourced. The methodology for estimating the subitem costs is similar to the methodology for estimating PV module cost. The cost estimates of subitems are propagated upward to the top-level BOM and used to calculate the direct material costs for the PV module. To estimate the direct labor costs, we use the sequence of

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processes specified for manufacturing and assembly of the module. We estimate the direct labor requirements based on plant capacity, labor ratios (labor requirement per equipment), and the number of units of equipment per process (see Equation (A6) in Appendix A). We defined a number of manufacturing processes for various PV technologies by consulting with experts. Such processes include sputtering and chemical vapor deposition processes for thin-film technology; for wafer technology, processes include wafer slicing and ribbon growth on substrate. Our implementation allows users to define and describe new manufacturing processes as needed. Each process in our model is described in terms of input, output, process constraints, and processing mechanisms. The input contains data about design specifications and input material information. The output contains data about process output, the next process step, and any waste generated. The processing constraints specify the conditions under which processing should take place (e.g., clean room environment, utility requirements). The processing mechanism contains information about equipment, processing rate, tooling, and labor. The overhead costs consist of fixed and variable overheads (see Figure 4). Fixed overhead costs comprise indirect materials, indirect labor, utilities, maintenance, and general plant overheads. These components depend on the design plant capacity; hence, we estimate them as a percentage of capital investment costs.

The capital investment costs for a manufacturing plant consist of equipment and facilities costs. The number of units of equipment required per production process is a function of design plant capacity, the production rate of the machine, and the annual effective operating hours (see Appendix A). To estimate the annual operating hours, we consider maintenance requirements, expected unplanned downtime, and worker availability. Facilities costs include the costs of installation, building and services, utilities equipment and installation, land and buildings, site development, engineering and supervision, working capital, and contingencies. We assume that equipment is dedicated to a specific technology and is not shared across other technologies, as is usually the case in the solar industry in which the manufacturing process for a given PV technology is unique.

We calculate the variable overhead costs based on process definitions and production volumes. The data required for estimating these costs come from process and equipment specifications, experience, and judgment of experts in these areas. Equations (A8)–(A12) in Appendix A give a brief explanation of the terms and the calculations for estimating these costs. After the cost estimates are applied and validated, the cost model gives the annual operating cost as output. We then obtain the unit module cost by dividing the annual operating costs by the expected module production in units (see Equation (A3)). The product cost is then reported in dollars per module and dollars per watt, which is a commonly used metric in the PV industry. The PV industry has been evolving rapidly; over the next several years, several factors, including learning effects, reduction in materials cost consumption, and increases in module efficiency, will influence the reduction in PV module costs. A few examples of ongoing cost reduction efforts are thinner wafers to reduce material consumption, better material handling of thin wafers to improve yield, larger thin-film modules, and improvements in module efficiency. Equation (A4) represents these effects as cost-reduction factors. Equation (A2) gives the revised product costs.

Our cost model has several advantages when compared with conventional approaches, including activity-based costing. First, it provides a tool for incorporating a desired level of product design and process design. Second, it provides a hierarchical approach to estimating costs in the PV module supply chain and a mechanism to collaboratively seek expert data. These results are used for cost projections and are also used for demand estimation and capacity planning, as we describe in the next sections.

## Demand Estimation

The objective of this module is to develop and implement a model that predicts the solar demand by year, region, and market type across the United States over the next 10 to 15 years. We adapt the market penetration and technology adoption models from the literature to estimate the demand for solar technology. Our work is an extension of prior work in this area by Navigant Consulting and the National Renewable

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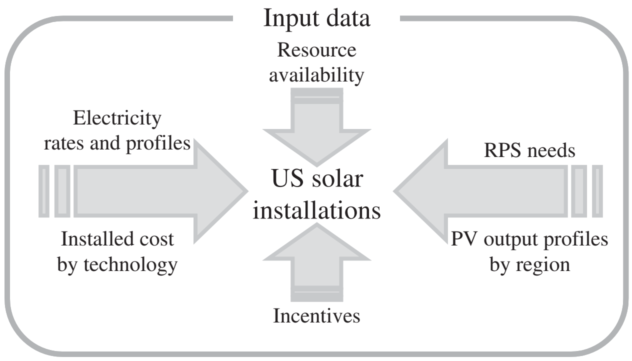


**Figure 5: To estimate the number of US installations by year, the demand estimation method requires the available rooftop space by region across the country, electricity rates by utility and by hour for each hour in the year, PV output profiles by hour and by region (which tell us the amount of power that is generated per watt of solar installation), installed cost by technology, federal and state incentives, and renewable portfolio standards (RPS) requirements by state.**

Energy Lab (see Paidipati et al. 2008). Their model estimates an average installation's cost and associated revenue generated. Using the cost and revenue estimates, the model computes the payback years of an investment in an average solar PV system. However, their model ignores the availability of financing, which has a significant impact on the demand for PV systems. We extend their model to include the effects of financing on demand. Figure 5 illustrates the data input that the demand estimation model requires.

The approach for estimating the market penetration follows. We first estimate the technical potential (i.e., the maximum number of megawatts that can physically be installed on rooftops by region of the country); we use the available floor space data to estimate this. We then estimate the revenues generated by an average rooftop installation, including annual savings on electric bills, additional revenues from net metering, and revenues from production incentives.

The next step in the algorithm is to compute the amount of time required to achieve payback on the investment. We first estimate system installation costs using module costs, capacity incentives, and investment tax credits. Using these installation costs and the revenues computed in the previous step, we compute the number of years needed for the net present value (NPV) of the investment to reach zero.

We then use market penetration curves (Bass 1969) that Paidipati et al. (2008) developed to obtain the percentage of market penetration as a function of payback years (see Figure 6). Multiplying this percentage by the maximum rooftop potential gives us the market penetration in MW as a function of payback years. The technology adoption curve (see Figure 6), which Paidipati et al. (2008) developed based on the model introduced by Fisher and Pry (1971), determines how this market penetration is achieved over the years. Many US states require utilities to generate a portion of their electricity using solar technologies as part of the RPS requirements. Our model ensures that the

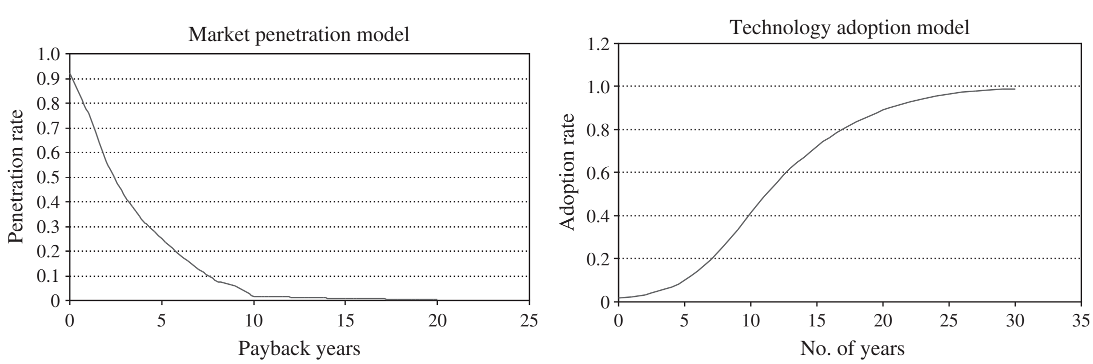


**Figure 6: The market penetration model gives the penetration of solar technology as a function of the payback years. The technology adoption curve determines how this penetration is achieved as a function of the number of years after market introduction.**

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predicted demand in these states is high enough to meet the RPS requirements.

## Capacity Planning

Determining the best production capacity expansion plan is an important strategic decision in most industries and is of crucial importance for a nascent solar business. Because the solar industry is affected by technology improvements, government policies, financing opportunities, intense competition, and a myriad of other factors, the planning process involves considerable uncertainty. Hence, we are faced with a capacity expansion problem with uncertainties in problem parameters over a number of periods.

One can model this problem using a multiperiod stochastic programming approach; however, it is computationally intractable for a large number of periods. Moreover, the probability density functions (PDFs) of the uncertain parameters are not available and are difficult to estimate. However, even if we could provide these estimates, convincing business executives of their validity would be difficult. In addition, solving problems using PDFs is computationally complex. Therefore, in our capacity planning, we use a novel scenario-based approach that is both computationally tractable and acceptable to management.

Our formulation makes it possible to incorporate a large number of parameters with uncertainties and solve a large-capacity planning problem in a way that avoids the curse of dimensionality. In addition, decision makers are more comfortable with a scenario-based analysis approach because of the flexibility it offers in modeling uncertainty; it describes the potential outcomes in any period using scenarios that management has defined. Moreover, that formulation allows users to add unknown parameters into scenarios, as business analysts identify them, in a convenient manner without sacrificing computational time.

We model the uncertainties in problem parameters including cost, demand, and competitive parameters (e.g., competitor pricing, market share, and margins over time by using scenarios, each of which have a specified probability). The users define the scenarios and assign probabilities to each. We assume the scenarios to be independent of one another. For example, in Table 1 we show three scenarios that use a few parameters that are uncertain in the real world. The actual scenarios consist of many more parameters.

We consider a discrete time planning horizon of 15 years with each period set to one year. We formulate the capacity planning problem as a scenario-based multiperiod linear programming problem as follows:

maximize Expected NPV of a capacity plan under all scenarios

subject to

Inventory constraints,

Capacity constraints,

Production constraints,

Budget constraints.

Appendix B shows the detailed mathematical formulation. The decision variables are the amount of capacity to be added and the amount of production in each period. The objective is to maximize the expected NPV over all scenarios. The inventory constraints model the inventory balance equation for each scenario and period. The production constraints limit

| | Scenario 1 ($p_1 = 0.2$) | | | Scenario 2 ($p_2 = 0.5$) | | | Scenario 3 ($p_3 = 0.3$) | | |
|---|---|---|---|---|---|---|---|---|---|
| Demand scenario | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| Demand (GW) | 1 | 2 | 3 | 10 | 15 | 20 | 5 | 8 | 12 |
| Price per module ($) | 550 | 500 | 450 | 500 | 400 | 300 | 450 | 350 | 250 |
| Cost ($) | 515 | 460 | 390 | 475 | 370 | 260 | 414 | 302 | 215 |
| Market share (%) | 8 | 7 | 6 | 10 | 11 | 12 | 7 | 9 | 10 |

**Table 1: These sample data illustrate how we construct the scenarios for capacity planning.** $p_n$**—Probability of scenario** $n$**.**

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production to the cumulative capacity installed at any period. The capacity constraints limit the expansion of capacity in each period. The budget constraints limit the cumulative budget available until a given period. Because this formulation is a linear program, we can use state-of-the-art commercial optimization solvers to solve it. Once we obtain the long-range capacity plan, we can generate detailed equipment plans for individual processes using the cost model.

The formulation described previously does not capture the risk involved in adopting a capacity plan. We compute that risk using the following risk measures: the risk of excess capacity (*CR*) and the risk of not meeting the business-required rate of return (*RR*).

During the planning stages, management sets thresholds for excess capacity ($C^T$) and rate of return ($R^T$) for planning purposes. The risk of not meeting these required thresholds is then calculated and compared across plans. See Equations (B7) and (B8) in Appendix B for calculations of *RR* and *CR*, respectively. Management weighs the risks associated with a particular capacity plan and uses these results to evaluate capital budgets to maximize the NPV while constraining the risk. Our model is used to answer the following questions:

1. What is the best capacity plan for each individual scenario?
2. How well does a plan that is optimal for a specific scenario work with respect to other scenarios?
3. Which plan maximizes the expected NPV?
4. What are the expected risks associated with a given capacity plan?
5. What are the NPVs and risks associated with a user-defined capacity plan?

## Implementation and Benefits

Developing models for cost estimation, demand estimation, and capacity planning was only part of our challenge. Making data entry, reporting, and evaluating alternatives easy and convenient was essential. We developed client–server systems to implement our models using Microsoft application development technology. The client systems run on user desktops, and the data required by the applications are stored in central relational databases that are located on servers.

Prior to the availability of our tools, information required to estimate and compare technology product alternatives resided with different individuals working in their respective technology groups. Hence, technology evaluations relied heavily on individual cost estimates, which the manufacturing technologists working in the respective technology groups provided. Incremental assumptions or formulaic changes by these technology groups on dozens of independent spreadsheets resulted in scale dissimilarity issues.

The cost model we developed paved the way for standardizing the data and the methodology by drawing on assumptions from a standardized database. It also helped the business to identify key cost drivers and evaluate new production processes. These tools have also helped GE Research in optimizing the design of the PV module to achieve the lowest installed PV system costs, plant sizing, and forecasting of individual installed cost components.

The integration of our tools allowed the business to capture information required to collaboratively estimate the costs and demand and reuse the captured information. This led to moving from dozens of spreadsheets to an integrated, standardized planning tool that reduced planning time from months to days (see Table 2), increased the understanding of key R&D programs, identified key variables for managing product costs, and evaluated capacity plans.

These tools also provide at-a-glance summarized information to users who are unfamiliar with the model. It allows a user to easily drill down and review assumptions, gain insight into the results, and provide feedback. Planning analysts have been using these tools to evaluate product costs, capital costs, and demand for various scenarios. They also use our tools to revise plans to adapt them to the changing business environment. Last year, the business used these tools to conduct a thorough analysis of the solar industry, which was presented to GE senior management to support major decisions in this space. Without the availability of these tools, it would have been extremely difficult to conduct this analysis.

Although we developed these tools for the solar industry, the methodology is portable to other industries, such as semiconductors and consumer durables, which require technological innovation and are bringing new products to the market. We are currently

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| Metric | Before model implementation | After model implementation |
|---|---|---|
| Person-hours required to cost and compare PV technology | >16 weeks | 1 week |
| Person-hours required to estimate demand for PV technology | >12 weeks | 2 weeks |
| Number of scenarios evaluated for finalizing plan | 3 | 8 |
| Business-planning cycle time for all scenarios | >16 weeks | 2 weeks |

**Table 2: Our models have resulted in substantial productivity improvements.**

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working with GE's licensing and trading group to identify opportunities to license the cost-modeling tool to other companies.

## Appendix A. Mathematical Formulation for Product Cost Estimation

We use the following notations.

**Sets**

$i$ index of the manufacturing process, $i = 1, 2, \ldots, I$.
$j$ index of the materials, $j = 1, 2, \ldots, J$.
$t$ index of the time period, $t = 1, 2, \ldots, T$.

**Parameters**

*Market demand*

$D_t$ demand for modules in watts at time $t$.

*Manufacturing plant*

$K_t$ capacity of the manufacturing plant in watts at time $t$.

*Installed system*

$S$ size of the PV power plant.

*PV module*

$\eta_t$ efficiency of a PV module at time $t$ in percentage.
$A_t$ surface area of the module used by the cells at time $t$ in $m^2$.
$R$ irradiance $R$ at standard test condition, 1,000 $W/m^2$.
$w_t = \eta_t \cdot A_t \cdot R$ output of a PV module in watts at time $t$.

*Materials*

$q_{ijt}$ quantity of material $j$ needed by process $i$ to make a unit of component at time $t$.
$y_{ijt}$ yield for material $j$ at process $i$ at time $t$.
$c_{ijt}$ cost of unit material $j$ at process $i$ at time $t$.
$m_{it} = q_{ijt} \cdot c_{ijt}/y_{ijt}$ total cost of material required for process $i$ at time $t$.

*Process*

$y^p_{it}$ production yield of process $i$ at time $t$.
$r_{it}$ production rate of individual equipment needed for process $i$ at time $t$.
$H_{it}$ annual effective operating hours for process $i$ at time $t$.
$N_t = D_t/w_t$ number of acceptable units from final production process $I$.

*Equipment*

$\alpha_{it}$ availability of equipment for process $i$ at time $t$.
$n_{it} = K_t/H_{it} \cdot \alpha_{it} \cdot r_{it} \cdot w_t$ number of units of equipment needed for process $i$ at time $t$.
$E_{it}$ cost of equipment units required for process $i$ at time $t$.

*Labor*

$l_{it}$ number of labor units per equipment needed for process $i$ at time $t$.
$C^{DL}_{it}$ annual direct labor cost per unit of labor at time $t$.

*Overhead*

$r_{SC}$ indirect materials (supplies) cost ratio.
$r_{MC}$ maintenance cost ratio.
$r_{GF}$ general fixed overhead ratio.

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*Cost reduction*

$\Delta TC_t^{PC}$ estimated reduction in total cost at time $t$ because of learning factor.

*Investment*

$I_t^E = \sum_i n_{it} E_{it}$ investment costs for equipment at time $t$.
$I_t^F$ investment costs for facilities at time $t$.
$I_t = I_t^E + I_t^F$ total capital investment costs at time $t$.

**Variables**

*Manufacturing plant*

$M_t^{PC}$ total materials cost at time $t$.
$L_t^{PC}$ total labor cost at time $t$.
$O_t^{PC}$ total overhead cost at time $t$.
$TC_t^{PC}$ total cost at time $t$.
$C_t^{PC}$ unit product cost at time $t$.

*Installed PV power plant*

$C_t^{IC}$ total installed cost for a PV system at time $t$.
$M_t^{IC}$ material cost for a PV system at time $t$.
$L_t^{IC}$ labor cost for a PV system at time $t$.
$O_t^{IC}$ overhead cost for a PV system at time $t$.

The total installed cost is given by

$$C_t^{IC}(S, C_t^{PC}) = F(S, M_t^{IC}) + F(S, L_t^{IC}) + F(S, O_t^{IC}), \quad \text{(A1)}$$

where $F(S, M_t^{IC})$, $F(S, L_t^{IC})$, and $F(S, O_t^{IC})$ are transfer functions that we developed for estimating $M_t^{IC}$, $L_t^{IC}$, and $O_t^{IC}$, respectively, for a PV system of size $S$. These transfer functions are beyond the scope of this paper.

Unit product cost is given by

$$C_t^{PC} = (TC_t^{PC} + \Delta TC_t^{PC})/D_t, \quad \text{(A2)}$$

where

$$TC_t^{PC} = M_t^{PC} + L_t^{PC} + O_t^{PC}. \quad \text{(A3)}$$

Let $\Delta M_t^{PC}$, $\Delta L_t^{PC}$, and $\Delta O_t^{PC}$ be the cost reductions in materials, labor, and overheads, respectively, resulting from improvements in the efficiency of cells, reduction in BOM cost, yield, or scaling factor or reduction in overheads. The transfer functions to estimate these cost reductions are also beyond the scope of this paper:

$$\Delta TC_t^{PC} = \Delta M_t^{PC} + \Delta L_t^{PC} + \Delta O_t^{PC}. \quad \text{(A4)}$$

Direct materials cost is given by

$$M_t^{PC} = \sum_{i=1}^{I} \left[ m_{it} \left( N_t \left( \prod_{k=i}^{I} y_{it}^p \right)^{-1} \right) \right]. \quad \text{(A5)}$$

Direct labor cost is given by

$$L_t = \sum_{i=1}^{I} \lceil l_{it} n_{it} \rceil C_{it}^{DL}. \quad \text{(A6)}$$

The project overhead costs are broken down in Figure 4. We provide the analytical structure for computing these costs:

$$O_t^{PC} = (OL_t + OS_t + OU_t + OM_t + OG_t). \quad \text{(A7)}$$

*Indirect labor* ($OL_t$). $OL_t$ can be broken down into support labor cost ($SL$), supervisor cost ($SU$), and payroll cost ($PR$). Support labor cost $C_t^{SL}$ and supervisor cost $C_t^{SU}$ are calculated using labor ratios. These labor ratios are obtained from previous manning tables, literature, and similar processes. A detailed personnel list is created, and the costs are computed accordingly:

$$OL_t = C_t^{SL} + C_t^{SU} + C_t^{PR}. \quad \text{(A8)}$$

*Indirect materials* ($OS_t$). $OS_t$ is dependent on the requirements of production equipment and facilities. It is calculated as a percentage of the $I_t$:

$$OS_t = r_{SC} \cdot I_t. \quad \text{(A9)}$$

*Utilities* ($OU_t$). Let $vu_{it}$ be the variable utilities cost per unit module for process $i$ at time $t$, and let $fu_t$ be the fixed utilities cost for the plant:

$$OU_t = \sum_{i=1}^{I} \left[ vu_{it} \left( N_t \left( \prod_{k=i}^{I} y_{kt}^p \right)^{-1} \right) \right] + fu_t. \quad \text{(A10)}$$

*Maintenance and services* ($OM_t$). $OM_t$ is dependent on the maintenance requirements of production equipment. It is calculated as a percentage of the $I_t$:

$$OM_t = r_{MC} \cdot I_t. \quad \text{(A11)}$$

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*General plant overhead* ($OG_t$). Let $OG_t$ represent the other general fixed overhead manufacturing costs. Such costs include capital depreciation, real estate taxes, insurance costs, royalties, contingency costs, distribution costs, and other general plant overheads. We calculate capital depreciation using a five-year, modified, accelerated cost recovery system (MACRS) (US Internal Revenue Service 2009) and the real estate taxes based on the manufacturing facility's real estate assessment and applicable state tax laws. The general plant overhead is a percentage of $I_t$:

$$OG_t = r_{GF} \cdot I_t. \tag{A12}$$

## Appendix B. Mathematical Formulation for Capacity Planning

**Sets**

$s$ scenario $s = 1, 2, \ldots, S$.
$t$ period $t = 1, 2, \ldots, T$.

**Parameters**

$p_s$ probability of scenario $s$.
$d_{st}$ demand in time $t$ under scenario $s$.
$r_{st}$ revenue per unit of product in time $t$ for scenario $s$.
$c_{st}$ cost per unit of product in time $t$ for scenario $s$.
$r_t^{\mathrm{TAX}}$ marginal tax rate.
$r^{\mathrm{DIS}}$ discount rate.
$r_s$ rate of return on investment for scenario $s$.
$c_t^{\mathrm{CAP}}$ unit cost of adding capacity at time $t$.
$h_t$ unit cost of holding inventory at time $t$.
$M_{\mathrm{MAX}}^{\mathrm{CAP}}$ maximum capacity addition at any given time.
$M^{\mathrm{INV}}$ maximum inventory allowed at any given time.
$M^{\mathrm{IVST}}$ maximum investment available for entire project.

**Variables**

$y_{st}$ production in time $t$ under scenario $s$, $y_{st} \geq 0$.
$q_{st}$ inventory in time $t$ under scenario $s$, $q_{st} \geq 0$.
$x_t$ capacity to be added in time $t$, $x_t \geq 0$.

We formulate the capacity planning problem as a linear program.

Maximize NPV

$$\sum_s \sum_t \frac{(r_{st} - c_{st})(1 - r_t^{\mathrm{TAX}})}{(1 + r^{\mathrm{DIS}})^t} y_{st} \cdot p_s - \sum_t \frac{c_t^{\mathrm{CAP}}}{(1 + r^{\mathrm{DIS}})^t} x_t - \sum_s \sum_t \frac{h_t}{(1 + r^{\mathrm{DIS}})^t} q_{st} \tag{B1}$$

subject to

(Inventory balance)

$$\begin{aligned} &q_{st} = q_{st-1} + y_{st} - d_{st} \quad \forall s,\ t = 1, \ldots, T, \\ &q_{s0} = 0, \\ &q_{st} \geq 0 \quad \forall s,\ t = 1, \ldots, T; \end{aligned} \tag{B2}$$

(Production constraint)

$$\sum_{i=1}^{t} x_i \geq y_{st} \quad \forall s,\ \forall t; \tag{B3}$$

(Maximum capacity addition)

$$x_t \leq M_{\mathrm{MAX}}^{\mathrm{CAP}} \quad \forall s,\ \forall t; \tag{B4}$$

(Maximum inventory)

$$q_{st} \leq M_t^{\mathrm{INV}} \quad \forall s,\ \forall t; \tag{B5}$$

(Maximum investment)

$$\sum_{i=1}^{t} c_t^{\mathrm{CAP}} x_t \leq M_t^{\mathrm{IVST}} \quad \forall s,\ \forall t. \tag{B6}$$

The model above is used to determine a capacity plan that maximizes the NPV. The risk measures used by management to assess the capacity plans generated using the above formulation are shown below. Expected rate-of-return risk (*RR*):

$$f^{RR} = \sum_s \max[R^T - r_s, 0] p_s. \tag{B7}$$

Expected excess-capacity risk (*CR*):

$$\begin{aligned} e_{st} &= \max\left[\sum_{i=1}^{t} x_i - d_{st}, 0\right], \\ f_s^{CR} &= \sum_t \max[e_{st} - C^T, 0], \\ f^{CR} &= \sum_s f_s^{CR} p_s. \end{aligned} \tag{B8}$$

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