Stochastic Optimization to Reduce Cost of Energy in Parabolic Trough Solar Power Plants

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THESIS

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ABSTRACT

The need for clean and cheap renewable energy is on the rise. Solar energy is one of the most clean and readily available technology with almost zero carbon emissions. Optimizing the resources to produce efficient power at low costs is the need of the day. In this thesis, we present a systematic method to optimize levelized cost of energy for 100 MW and 500 MW power plants. We use SAM, which is a simulation software to study the parabolic trough solar technology in detail and define the decision variables and uncertain variables for the problem. Then we use BONUS which is an optimization algorithm to optimize the cost using the samples of these variables. This thesis analyzes the differences between the optimal and base solutions and shows the effect of uncertainty on the results. We present the optimal values for the various technical parameters which gives us the least cost of energy.

Keywords: optimization under uncertainty, SAM, BONUS, parabolic trough solar technology, levelized cost of energy

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1 Introduction

Energy crisis and climate change are two different terms but closely related. The need for energy is rising by the day due to the increase in demand of developing countries like India and China. At the same time, the effects of using fossil fuels for producing energy are increasingly evident. The global average temperature has increased by 0.76°C (0.57°C to 0.95°C) between 1850 to 1899 and 2001 to 2005, and the warming trend has increased significantly over the last 50 years (IPCC, 2007b). Sea-levels are rising at an alarming rate and deserts are expanding in the subtropics. These are just some of the glaringly obvious consequences of increase in greenhouse gas emissions over the years. And the main contributors to this increase are fossil fuels. The solution to this is using alternative, less harmful and sustainable energy sources. The use of renewable energy sources like solar, biomass, wind, geothermal has been on the rise in the last decade.

Although efforts are being made to increase use of these sources, renewable energy still accounted for 11.1% of total energy generation in the United States in 2015. Hydropower contributed to about 6.14% of the total U.S electricity generation in 2015, whereas wind power was the source of almost 4.67% of U.S electricity generation in 2015. Biomass and geothermal power provided about 1.57% and 0.41% of U.S electricity generation in 2015, respectively. Solar power accounts for less than 1% of the electricity generated in the United States in 2015. Projections vary, but scientists have advanced a plan to power 100% of the world's energy with wind, hydroelectric, and solar power by the year 2030. (Wikipedia, 2013)

In my thesis, I have been working on how to optimize cost in a solar energy power plant, hence, I will be further discussing solar technologies in detail.

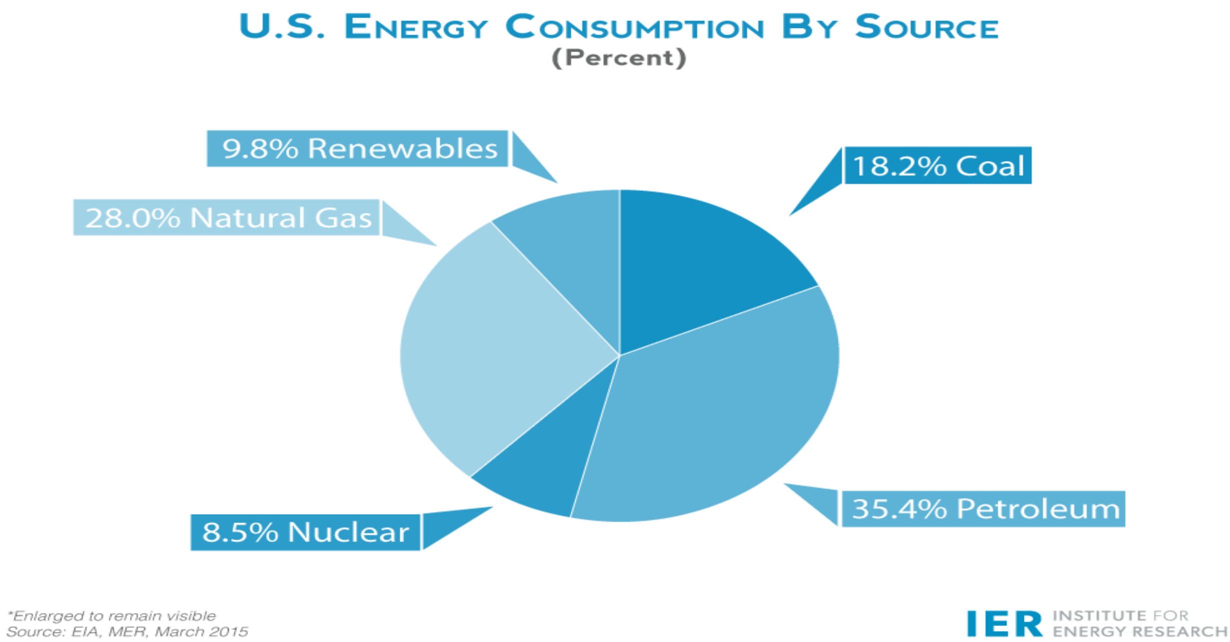


Figure 1. Distribution of energy consumption in United States in 2015 by source

(EIA, MER, March 2015)

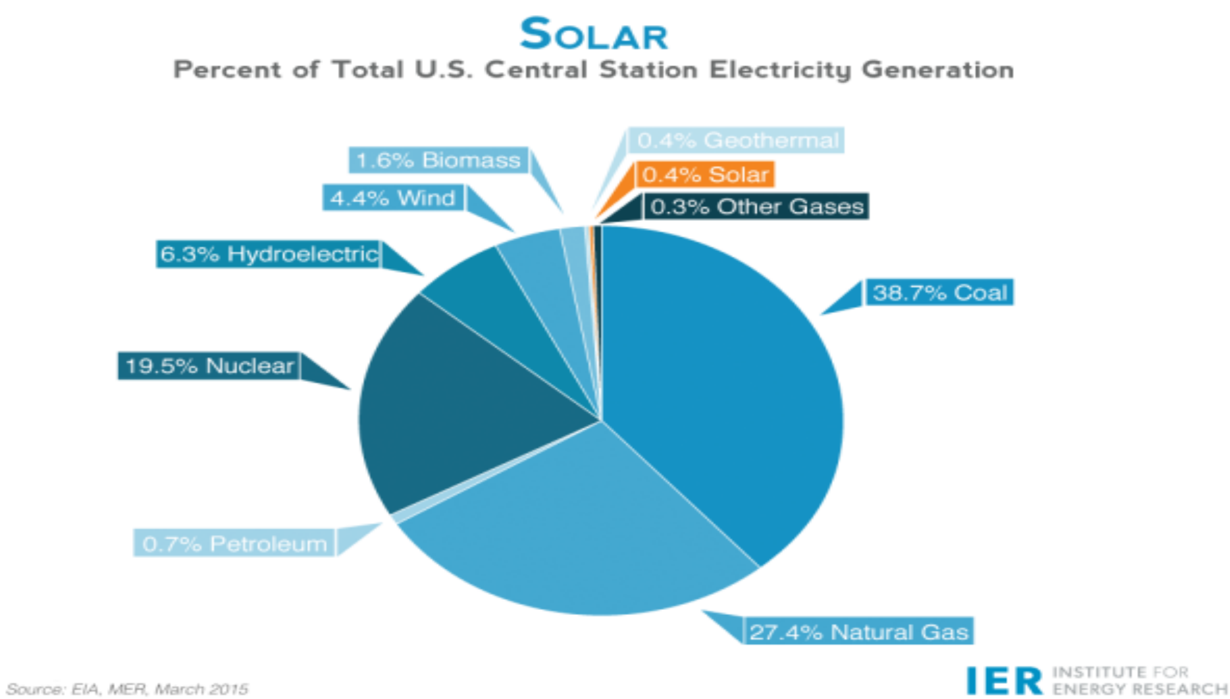


Figure 2. Solar energy contributed to only 0.4% of the total electricity generation in U.S. in 2015

(EIA, MER, March 2015)

1.1 Solar Technologies

Solar energy is the cleanest, most abundant renewable energy source available. The U.S. has some of the world's richest solar resources. Today's technology allows us to harness this resource in several ways, giving the public and commercial entities flexible ways to employ both the light and heat of the sun.

There are three primary technologies by which solar energy is commonly harnessed: photovoltaics (PV), which directly convert light to electricity; concentrating solar power (CSP), which uses heat from the sun (thermal energy) to drive utility-scale, electric turbines; and heating and cooling systems, which collect thermal energy to provide hot water and air conditioning.

Solar energy can be deployed through distributed generation (DG), whereby the equipment is located on rooftops or ground-mounted arrays close to where the energy is used. Some solar technologies can also be built at utility-scale to produce energy as a central power plant.

Photovoltaic (PV) - These solar technologies directly produce electricity which can be used, stored, or converted for long-distance transmission. PV panels can be manufactured using a variety of materials and processes and are widely-used for solar projects around the world.

Solar Heating and Cooling (SHC) - These technologies generate thermal (heat) energy for water & pool heating and space heating. Solar heating technologies are cost-effective for customers in a variety of climates.

Concentrating Solar Power (CSP) - Using reflective materials like mirrors and lenses, these systems concentrate sunlight to generate thermal energy, which is in turn used to generate electricity. Similar to traditional power plants, many CSP plants are hundreds of megawatts (MW) in size and some can continue to provide power after sunset.

Since we are looking to optimize cost in a large scale power plant, we will be focusing more on concentrating solar power technologies further.

1.2 Different types of Concentrating Solar Power Technologies

CSP technologies include parabolic trough, linear Fresnel reflector, power tower, and dish/engine systems.

1.2.1 Parabolic Trough

A parabolic trough system is a type of concentrating solar power (CSP) system that collects direct normal solar radiation and converts it to thermal energy that runs a power block to generate electricity. The components of a parabolic trough system are the solar field, power block, and in some cases, thermal energy storage and fossil backup systems. The solar field collects heat from the sun and consists of parabolic, trough-shaped solar collectors that focus direct normal solar radiation onto tubular receivers. Each collector assembly consists of mirrors and a structure that supports the mirrors and receivers, allows it to track the sun on one axis, and can withstand wind-induced forces. Each receiver consists of a metal tube with a solar radiation absorbing surface in a vacuum inside a coated glass tube. A heat transfer fluid (HTF) transports heat from the solar field to the power block (also called power cycle) and other components of the system. The power block is based on conventional power cycle technology, using a turbine to convert thermal energy from the solar field to electric energy. The optional fossil-fuel backup system delivers supplemental heat to the HTF during times when there is insufficient solar energy to drive the power block at its rated capacity.

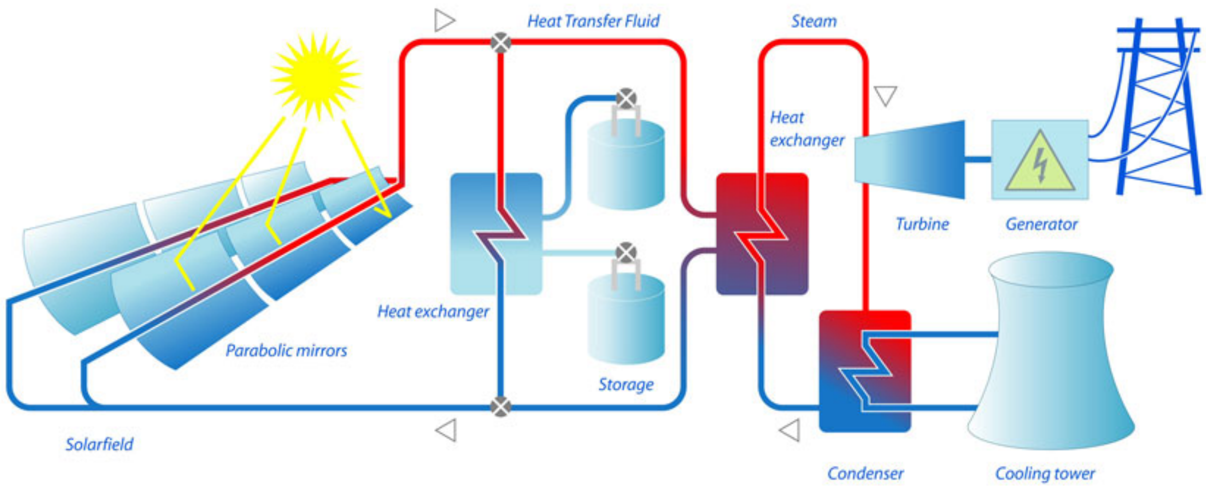


Figure 3. Working principle of a parabolic trough power plant

1.2.2 Power Tower Technology

A power tower system (also called a central receiver system) is a type of concentrating solar power (CSP) system that consists of a heliostat field, tower and receiver, power block, and optional storage system. The field of flat, sun-tracking mirrors called heliostats focus direct normal solar radiation onto a receiver at the top of the tower, where a heat-transfer fluid is heated and pumped to the power block. The power block generates steam that drives a conventional steam turbine and generator to convert the thermal energy to electricity. (SAM Manual, 2014)

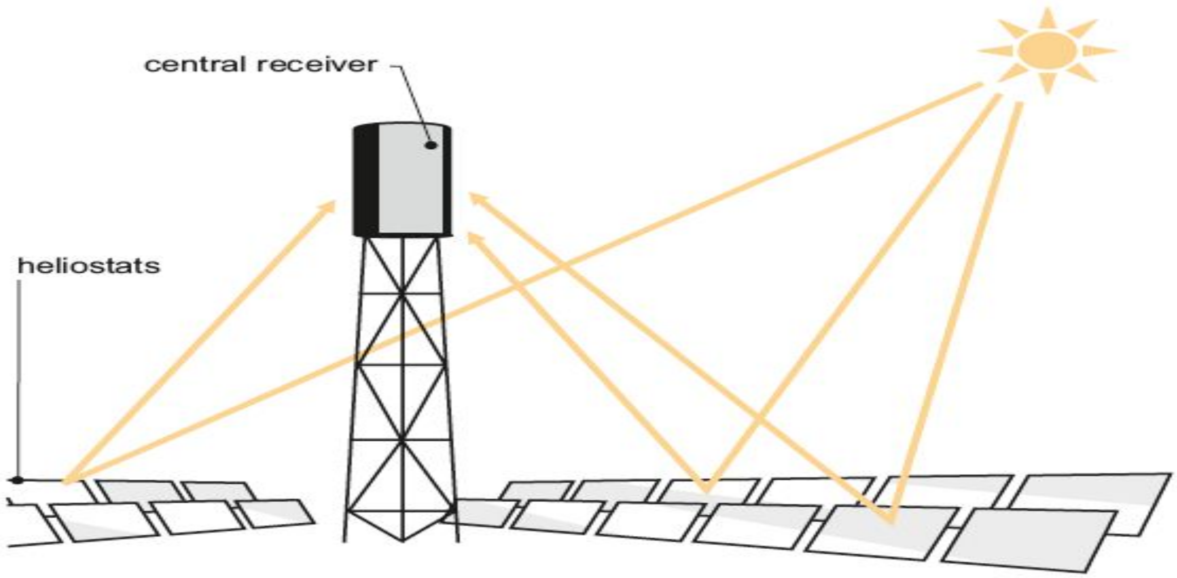


Figure 4. Working principle of power tower technology

1.2.3 Linear Fresnel

Linear Fresnel reflectors use long, thin segments of mirrors to focus sunlight onto a fixed absorber located at a common focal point of the reflectors. These mirrors are capable of concentrating the sun's energy to approximately 30 times its normal intensity. This concentrated energy is transferred through the absorber into some thermal fluid (this is typically oil capable of maintaining liquid state at very high temperatures). The fluid then goes through a heat exchanger to power a steam generator.

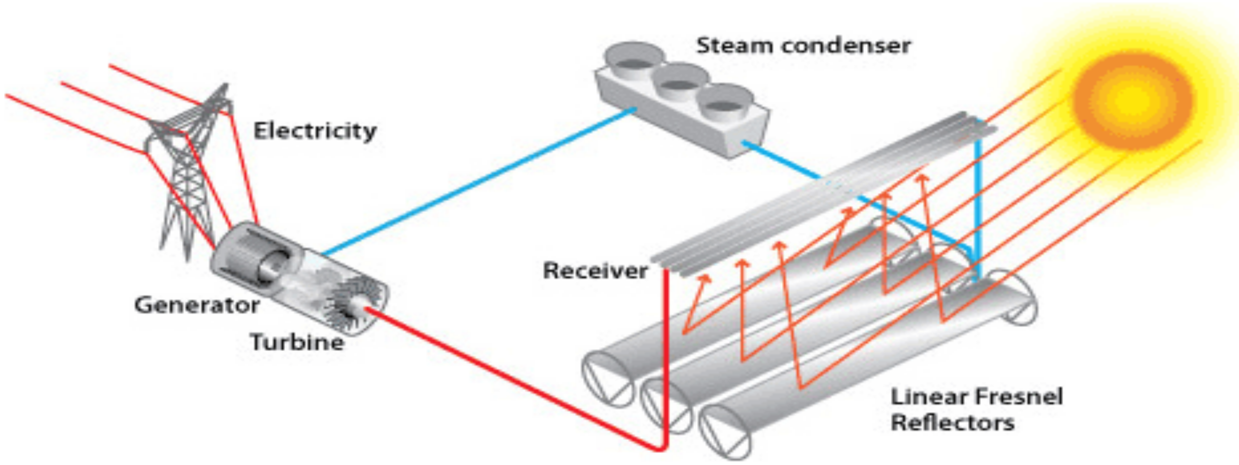


Figure 5. Linear Fresnel Reflector

1.2.4 Dish Stirling

A dish-Stirling system is a type of concentrating solar power (CSP) system that consists of a parabolic dish-shaped collector, receiver and Stirling engine. The collector focuses direct normal solar radiation on the receiver, which transfers heat to the engine's working fluid. The engine in turn drives an electric generator. A dish-Stirling power plant can consist of a single dish or a field of dishes. (SAM Manual, 2014)

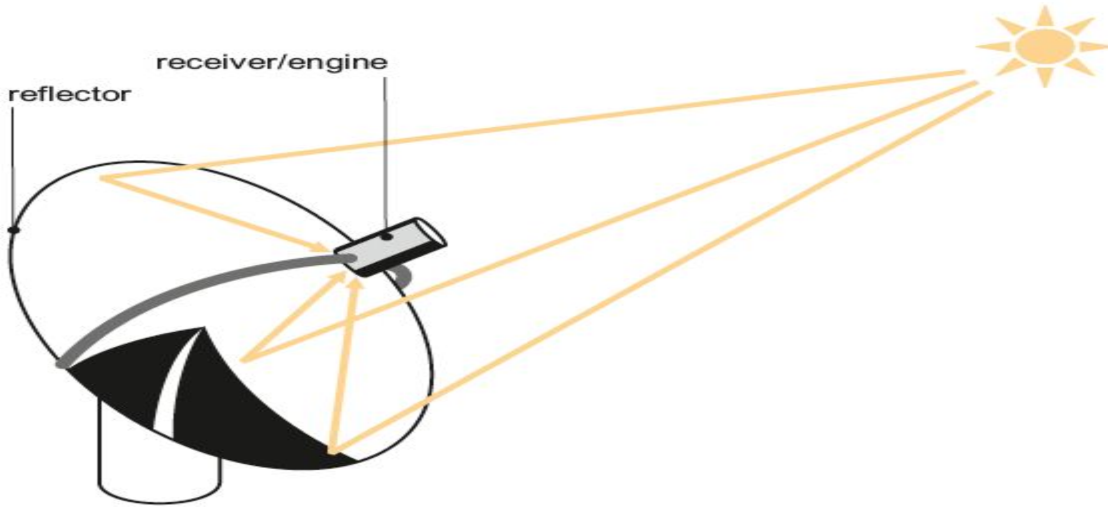


Figure 6. Working principle of dish/stirling engine powered technology

1.3 Optimization and the role of uncertainty

Optimization plays a new role in new solar technologies. The thing that has been holding back solar thermal technologies from really dominating the renewable energy sector is the cost of the technology. The cost of equipment, land, labor sometimes makes it infeasible for these solar thermal power plants to function for a longer period of time. Since CSP plants depend on solar radiation, they require large areas of land and amicable weather conditions for efficient electricity output. These are some of the drawbacks of the CSP technology and that is where optimization comes in. Optimizing the resources to get the most optimal and efficient output within the lowest cost is the need of the day.

An optimization algorithm for the calculation of electricity unit cost from various power generation technologies was developed by Andreas Poullikkas (Poullikkas, 2001). The algorithm takes into account the capital cost, fuel cost, operation and maintenance requirements of each candidate scheme and calculates the least cost configuration and ranking order of candidate power technologies. This algorithm was then used to conduct an economic analysis to investigate whether it is feasible to install a parabolic trough solar thermal plant in Cyprus (Poullikkas, 2009). The analysis includes varying few parameters of the plant to carry out a parametric cost-benefit analysis to identify the least cost feasible option.

China's solar thermal power development was studied by Zhifeng Wang (Wang, 2010). The study describes a roadmap for development between 2006 and 2025 by identifying the key factors for the successful commercialization of solar thermal technologies. India, another fast developing country, is yet to gain experience in setting up large-scale commercially viable solar thermal power plants (Pidaparthi and Prasad, 2013). The problems faced in setting up the first parabolic trough power plant (1 MW) developed by IIT Mumbai were studied and this helped in identifying the critical components of the plant.

As we know, a parabolic trough plant is made up of a lot of components. By breaking down the plant into the vital elements, and optimizing the efficiency of each element individually, we can optimize the overall efficiency of the plant. For example, collectors are a significant constituent of the parabolic trough technology, and recognizing a way to optimize the output of the collectors can help in improving the plant's efficiency. The development of Ultimate Trough collector aided in reducing the levelized cost of electricity of CSP plants (Riffelmann et al., 2014). Parabolic trough collectors (PTC) are also often employed for solar steam generation (Kalogirou et al., 1997). This steam generated is used in stead of the the heat transfer fluid, to drive the turbine in the power block to generate electricity. Kalogirou et al. optimized the PTC steam generation system to minimize the system startup energy requirement using the PTCDES modelling program.

The need for lower investment and energy costs leads to a demand for higher operating temperatures in plant cycle (Ruegamer et al., 2014). Use of molten salts withstanding up to 550 degrees Celsius are considered for use in CSP plants. Due to different thermodynamic boundary conditions between salts and thermal oil, other plant parameters change such as storage, collector and receiver design which impacts energy output. In various simulation steps, different scenarios of solar power plant design are discussed taking into consideration, parameters like solar field size, site conditions, type of heat transfer fluid, dimensioning of parabolic trough collector, absorber-tube coating and diameters as well as storage tank sizes to show effects on levelized cost of electricity. Goal of simulation work is to show effect of a major technology step by introducing improved solar field components resulting in higher operation temperatures at adapted thermal losses.

The size of the solar field is pivotal to the electricity production and cost of a CSP plant. Too big a field can unnecessarily increase the cost and too small a field might just suffice the part-load conditions for the power block. (Montes et al., 2009) Hence, optimizing the size of the solar field can ease the cost of energy in solar thermal plants. Montes et al. present a methodology for economic optimization of the solar multiple in parabolic trough plants. Solar multiple is the ratio between thermal power produced by the solar field at design point and thermal power required by the power block at nominal conditions. That is, it represents solar field size related to the power block in terms of nominal thermal power. Five plants are considered (no thermal storage), and by keeping the parameters for power block consistent, they vary the solar field size to calculate the solar multiple for which the levelized cost of energy is minimum. It is concluded that the optimum solar multiple depends on plant location, design point and power cycle parameters at nominal conditions, besides the solar field size.

1.4 Problem formulation and motivation

The motivation behind the thesis is, despite many efforts at using optimization models to improve the efficiency of different concentrated solar power plants, people haven't looked into including uncertainties involved in using these technologies. Using the algorithmic framework (BONUS algorithm) developed by Dr. Diwekar and Amy David and using the System Advisor Model (SAM) simulation software developed by National Renewable Energy Laboratory (NREL) we present a systematic stochastic optimization methodology to reduce the levelized cost of energy under power constraints in parabolic trough solar power plants. The problem statement can be defined as:

Minimize E(LCOE)

subject to

Power = constant

We use SAM to simulate the technical and financial parameters of the power plant which helps us in identifying the decision variables and uncertain variables involved in our problem. Then we use the BONUS algorithm framework to optimize these decision variables including the uncertainties to get our lowest cost objective function. We have selected San Diego, California as the test location for the parabolic trough plant to be situated. San Diego is a prime location to set up a power plant because of the ideal climate conditions. We test the methodology on 2 different power plant capacities so as to compare our results efficiently.

The problem function, SAM software and the BONUS algorithm all will be elaborated in the chapters ahead.

2 Introduction to System Advisor Model

2.1 Overview of SAM

The System Advisor Model (SAM) is a simulation model designed to perform financial and performance related calculations using various design and cost parameters for grid-connected power projects based on different types of renewable sources of energy. This is a highly resourceful tool for people working in the renewable energy sector. SAM was developed by the National Renewable Energy Laboratory (NREL) in collaboration with Sandia National Laboratories.

The basic concept behind SAM is it uses various technical parameters such as type of equipment, design of equipment, configuration of the system as inputs to make performance predictions which then enable it to make cost of energy estimates using financial variables such as installation costs, labor costs, operation and maintenance costs. It gives you an idea of what, which and how much of the resources are exactly required to set up a successful and economically viable power plant based on a renewable source of energy.

SAM represents the cost and performance of renewable energy projects using computer models developed at NREL, Sandia National Laboratories, the University of Wisconsin, and other organizations. Each performance model represents a part of the system and each financial model represents a project's financial structure. The models require input data to describe the performance characteristics of physical equipment in the system and project costs. (SAM Manual, 2014)

SAM also requires a weather data file describing the renewable energy source and weather conditions at the project location.

2.2 Performance Models

SAM's performance models run hourly simulations to calculate the power system's electrical output. The sum of these values is the total annual output that the financial models uses to calculate the project annual cash flow and financial metrics.

It includes the following performance models based on different renewable sources of energy:

- Photovoltaic Systems
- Concentrating Solar Power
- Generic System
- Solar Water Heating
- Wind Power
- Geothermal
- Biomass Power

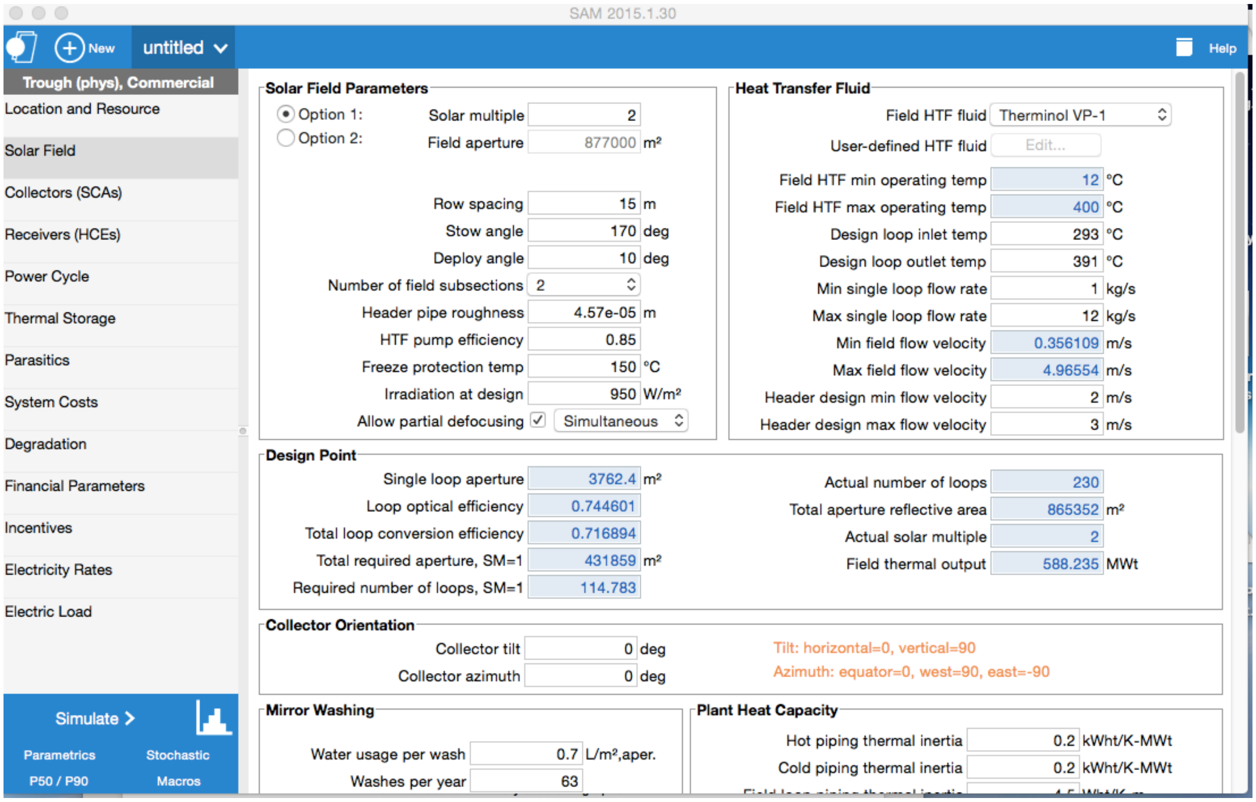


Figure 7. Input tab for the CSP Parabolic Trough performance model

2.3 Financial Models

SAM's financial models calculate a project's cash flow over an analysis period that you specify. The cash flow determines the value of electricity generated by the system and incentives, and the cost of installation, operation and maintenance, taxes, and debt. (SAM Manual, 2014)

The financial models can represent two main types of projects:

- Residential and commercial projects that buy and sell electricity at retail rates and displace purchases of power from the grid
- Power Purchase Agreement (PPA) projects that sell electricity at a wholesale rate to meet internal rate of return requirements

2.4 Weather Data

SAM uses weather data to describe the location, the characteristics of the renewable energy source. The data is used from SAM's database library which is installed automatically with the software itself. The performance models use this data to represent the resource and the ambient weather conditions which affect the system's output. Location information such as the area coordinates, wind speed, average temperature and elevation about sea level are stored in these weather files.

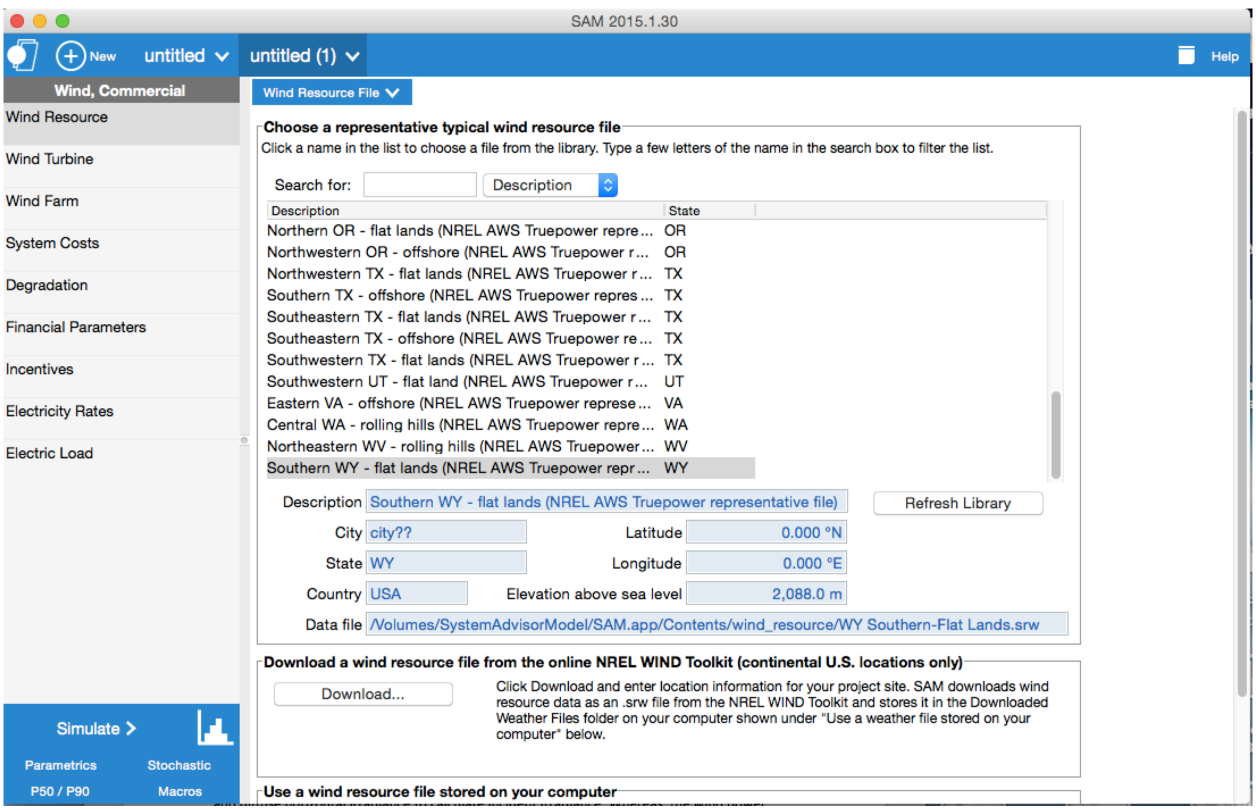


Figure 8. Wind Resource tab on the input screen showing a list of different locations and their weather characteristics

The weather data elements differ for each performance model. For example, for the solar technologies, the weather file consists of data elements such as global horizontal, direct normal and diffuse horizontal irradiance to calculate incident irradiance. Whereas, the wind power performance model requires wind speed and temperature data at three different heights above the ground along with wind direction and atmospheric pressure data. The biomass power model uses information from many databases of feedstock data for the United States. The geothermal model, accesses a database of temperature and depth data for the geothermal resource.

The SAM weather file is a text file which contains one year of hourly data. A weather file may contain typical-year data that represents long-term historical data or single-year data for a particular year. Typical-year data is data consisting of 12 months out of a multi-year period which best represents the renewable source and weather conditions for that location. For example, a typical year file developed from a data set for the years 2000-2010, could use data from 2003 for January, 2006 for February, 2001 for March etc. It can be thought of as an average of the original year over a historical period, but it is much more accurate to say that the data is *typical* because the methods involve more than just calculating average values. For long-term economic analysis, it is more suitable to use the annual simulation results using typical year weather data. Single-year data depicts the weather conditions of the location for a single particular year. It is more appropriate to use this weather file when you are not using the results to predict the economic value over many years.

The sources for the data in the weather files in SAM's solar resource library are NREL's National Solar Resource Database, Solar and Wind Energy Resource Assessment Programme, The ASHRAE International Weather for Energy Calculations Version 1,1 and Canadian Weather for Energy Calculations. For Wind Resources, the wind data files are developed for NREL by AWS Truepower. SAM also allows the user to download weather data files for a particular zip code, latitude and longitude, address from its NREL Solar Power Prospector database and NREL Wind Integration datasets. Also, there is an option to create your own weather file with your own data.

It can read weather data from any file from any source as long as it is in one of the recognizable formats without any formatting errors, gaps in the data, or invalid values.

2.5 Results

SAM displays simulation results using tables and graphs. The metrics table displays the project's net present value, annual energy production, internal rate of return and other single-value metrics. There is also the detailed annual cash flow and hourly performance data that can be viewed in tabular or graphical form.

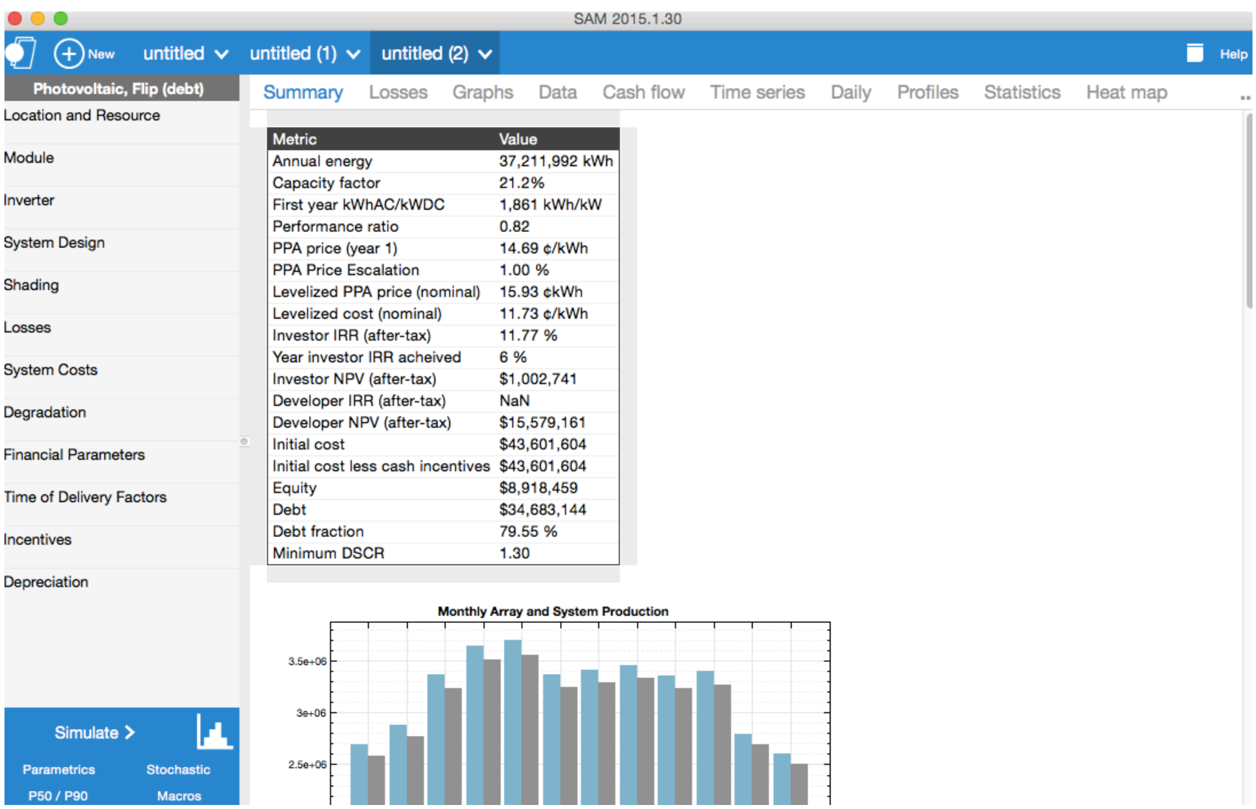
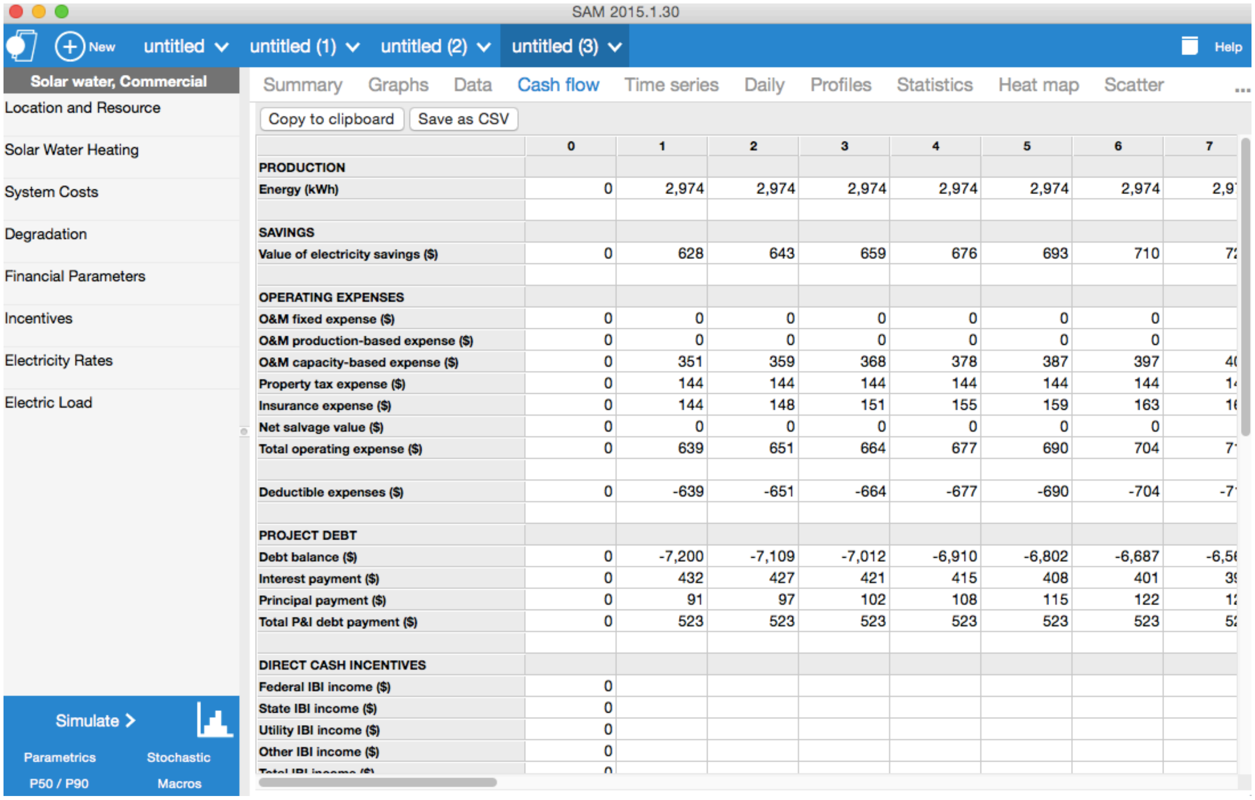


Figure 9. Results page displaying performance and financial metrics for a Photovoltaic power plant using a PPA partnership with debt financial mode



	0	1	2	3	4	5	6	7
PRODUCTION								
Energy (kWh)	0	2,974	2,974	2,974	2,974	2,974	2,974	2,9
SAVINGS								
Value of electricity savings ($)	0	628	643	659	676	693	710	7
OPERATING EXPENSES								
O&M fixed expense ($)	0	0	0	0	0	0	0	
O&M production-based expense ($)	0	0	0	0	0	0	0	
O&M capacity-based expense ($)	0	351	359	368	378	387	397	4
Property tax expense ($)	0	144	144	144	144	144	144	1
Insurance expense ($)	0	144	148	151	155	159	163	1
Net salvage value ($)	0	0	0	0	0	0	0	
Total operating expense ($)	0	639	651	664	677	690	704	7
Deductible expenses ($)	0	-639	-651	-664	-677	-690	-704	-7
PROJECT DEBT								
Debt balance ($)	0	-7,200	-7,109	-7,012	-6,910	-6,802	-6,687	-6,5
Interest payment ($)	0	432	427	421	415	408	401	3
Principal payment ($)	0	91	97	102	108	115	122	1
Total P&I debt payment ($)	0	523	523	523	523	523	523	5
DIRECT CASH INCENTIVES								
Federal IBI income ($)	0							
State IBI income ($)	0							
Utility IBI income ($)	0							
Other IBI income ($)	0							

Figure 10. Cash flow of a solar water heating project using a commercial financial model

A built-in graphing tool showcases a set of default graphs and allows for creation of custom graphs. All graphs and tables can be exported in various formats for inclusion in reports and presentations, and also for further analysis with spreadsheet or other software.

2.6 Analysis Options

In addition to simulating a system's performance over a single year and calculating a project cash flow over a multi-year period, SAM's analysis options make it possible to conduct studies involving multiple simulations, linking SAM inputs to a Microsoft Excel workbook, and working with custom simulation modules. The following options are for analyses that investigate impacts of variations and uncertainty in assumptions about weather, performance, cost, and financial parameters on model results:

- Parametric Analysis: Assign multiple values to input variables to create graphs and tables showing the value of output metrics for each value of the input variable. Useful for optimization and exploring relationships between input variables and results.
- Stochastic Simulation: Assign multiple values to input variables using statistical distributions to study the effect of uncertainty on output metrics.

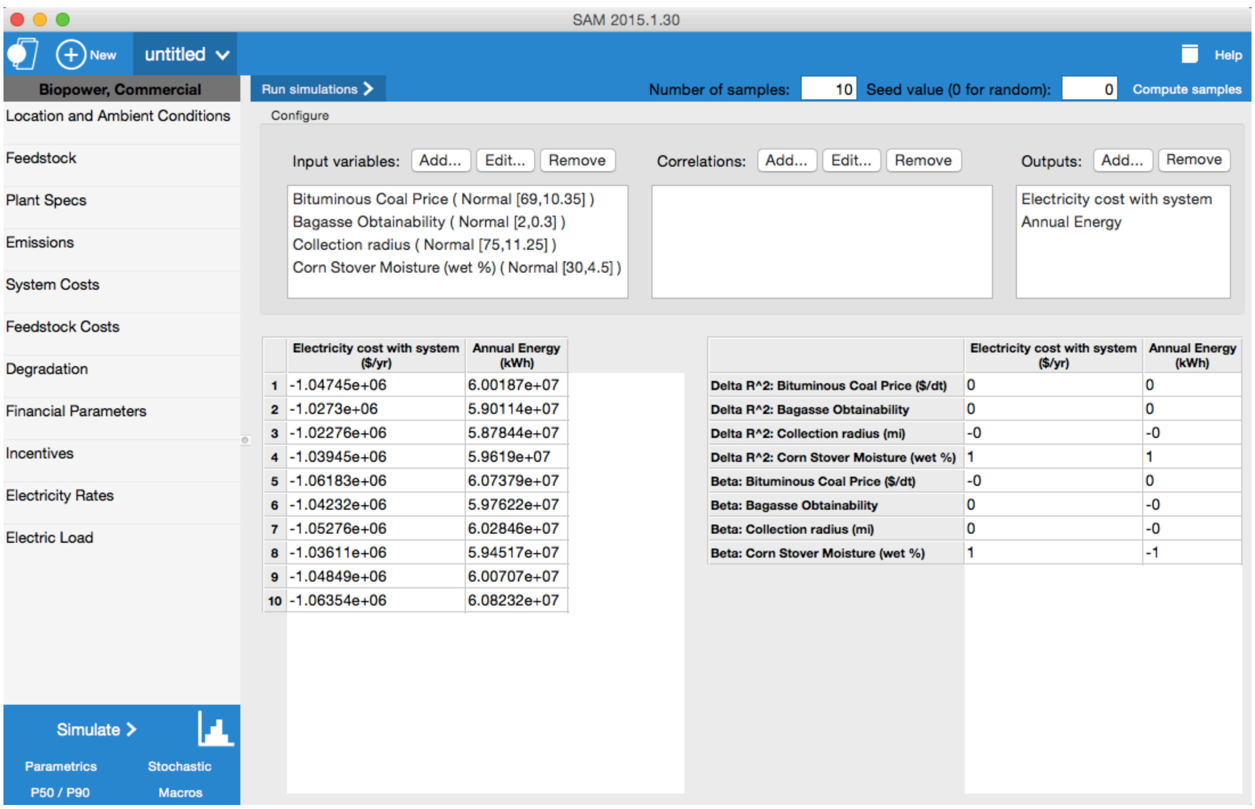


Figure 11. Stochastic optimization using the stochastic analysis feature for a Biomass combustion model showing the effect of few decision variables on different output metrics

- P50/P90: The probability exceedance analysis involves running a set of single-year simulations to calculate annual output values, and then from those values determining the output value that was exceeded 50% of the time (P50 value) and the value that was exceeded 90% of the time (P90 value).
- Macros: SAM's scripting language LK allows you to write your own scripts within the SAM user interface to control simulations, change values of input variables, and write data to text files. (SAM, 2014)
- Excel Exchange: External models developed in Excel can be accesses using this feature which allows Excel to calculate the value of input variables, and automatically pass values of input variables between SAM and Excel. (SAM, 2014)

2.7 Model Structure

SAM's model consists of a user interface, a simulation engine and a programming interface. User interface is the screen which we see. It lets you choose the input variables for the performance and financial models. It also allows you to choose advanced analysis options such as the parametric analysis and stochastic analysis. And it displays the final results of the simulation in tabular and graphical forms. The simulation or calculation engine is the core processor. It uses all the input values to perform time-step-by-time-step simulation of a power system's performance, and a set of annual financial calculations to generate the project's cash flow over multiple years and other financial metrics. The programming interface lets other external programs to interact with SAM. (SAM Manual, 2014)

2.8 Problem formulation

In the previous chapter, the problem statement was defined as:

Minimize E(LCOE)

subject to

Power = constant

From this definition, the objective function and constraint are known. Since SAM is a black box model, the objective function cannot be defined using an algebraic expression. Hence, we cannot identify the decision variables in the problem statement itself. Also, since this is a stochastic optimization problem, the problem statement also consists of uncertain variables. Both the decision variables and uncertain variables are defined using the parameters provided by SAM for their 'CSP Parabolic Trough (Physical)' performance model and the 'Commercial' financial model. The constraint value for the power capacity of the plant is also fixed at 100 MW.

Thus, the problem can be re-formulated as:

Minimize E(LCOE)

subject to

Power = 100 MW

A further analysis is carried out for setting-up a bigger power plant with a bigger capacity of 500 MW where the constraint value for the power capacity is fixed at 500.

2.8.1 Decision Variables

The parameters for Parabolic Trough physical model in SAM are divided into different pages as per their classification. (SAM Manual, 2014)

A) **Solar Field** - The Solar Field page displays variables and options that describe the size and properties of the solar field, properties of the heat transfer fluid. It also displays reference design specifications of the solar field.

B) **Collectors** - A collector (SCA, solar collector assembly) is an individually tracking component of the solar field that includes mirrors, a supporting structure, and receivers. On the Collectors page, you can define the characteristics of up to four collector types.

C) **Receivers** - A receiver (HCE, heat collection element) is a metal pipe contained in a vacuum within glass tube that runs through the focal line of the trough-shaped parabolic collector. Seals and bellows ensure that a vacuum is maintained in each tube. Anti-reflective coatings on the glass tube maximize the amount of solar radiation that enters the tube. Solar-selective radiation absorbing coatings on the metal tube maximize the transfer of energy from the solar radiation to the pipe. On the Receivers page, you define the characteristics of up to four receiver types.

D) **Power Cycle** - The power cycle model represents a power block that converts thermal energy delivered by the solar field and optional thermal energy system to electric energy using a conventional steam Rankine cycle power plant. The power cycle can use either an evaporative cooling system for wet cooling, or an air-cooled system for dry cooling. The power cycle may include a fossil-fired backup boiler that heats the heat transfer fluid before it enters the power cycle during times when there is insufficient solar energy to drive the power cycle at its design load.

E) **Thermal Storage** - A thermal energy storage system (TES) stores heat from the solar field in a liquid medium. Heat from the storage system can drive the power block turbine during periods of low or no sunlight. A thermal storage system is beneficial in many locations where the peak demand for power occurs after the sun has set. Adding thermal storage to a parabolic trough system allows the collection of solar energy to be separated from the operation of the power block. For example, a system might be able to collect energy in the morning and use it to generate electricity late into the evening.

F) **Parasitics** - The variables on the Parasitics page define electrical loads in the system. For each hour of the simulation, SAM calculates the parasitic load and subtracts it from the power cycle's gross electrical output to calculate the net electrical output.

We target the Solar Field parameters for choosing the decision variables for our problem. To determine the decision variables from all the solar field parameters, we performed a sensitivity analysis to see the effect of these parameters on the annual energy calculated by the model. The results of the sensitivity analysis are shown below:

		Annual Energy (kWh)
Default Value		251,600,544
Parameters Varied		
Solar Multiple	3	364,801,440
	1	119,886,016
Row Spacing	5 meters	160,022,736
	30 meters	252,690,096

Stow Angle	140 degree	196,597,888
	180 degree	255,226,672
Deploy Angle	0 degree	255,529,168
	30 degree	233,280,784
No. of field subsections	4	255,900,912
	8	252,085,568
Header pipe roughness	4.57e-0.6m	255,408,624
	4.57e-0.4m	254,458,531
HTF pump efficiency	0.25	242,410,192
	0.75	254,698,123
Freeze protection temperature	250 degree Celsius	121,678,136
	120 degree Celsius	298,428,152
Irradiation at design	1500 W/m^2	151,818,640
	700 W/m^2	311,865,344
Design loop inlet temperature	193 degree Celsius	277,526,528
	250 degree Celsius	265,036,630
Design loop outlet temperature	350 degree Celsius	226,445,179
	491 degree Celsius	241,098,336
Minimum single loop flow rate	3 kg/s	250,610,944
	5 kg/s	255,563,438
Maximum single loop flow rate	7 kg/s	228,587,728
	16 kg/s	224,093,184
Header design minimum flow velocity	1 m/s	253,604,000

	3 m/s	254,126,000
Header design maximum flow velocity	5 m/s	255,565,000
	12 m/s	257,342,000
Collector tilt	0 deg.	251,600,544
	10 deg.	91,179,560
Collector azimuth	0 deg.	251,600,544
	10 deg.	243,758,192
Water usage per wash	0.7 L/m^2,aper.	251,600,544
	4 L/m^2,aper.	251,600,544
Washes per year	63	251,600,544
	100	251,600,544
Hot piping thermal inertia	0.2 kWht/K-MWt	251,600,544
	1.2 kWht/K-MWt	251,600,544
Cold piping thermal inertia	0.2 kWht/K-MWt	251,600,544
	1.2 kWht/K-MWt	251,600,544
Field loop piping thermal inertia	3 Wht/K-m	251,600,544
	9 Wht/K-m	251,600,544

Table 1. Sensitivity Analysis

So as we can see which variables have the maximum effect on annual energy, we select those as our decision variables. (SAM Manual, 2014) These are the decision variables:

Solar multiple: The field aperture area expressed as a multiple of the aperture area required to operate the power cycle at its design capacity. A solar multiple value of one represents the solar field aperture area that, when exposed to solar radiation equal to the design radiation value, generates the quantity of thermal energy required to drive the power block at its rated capacity, accounting for thermal and optical losses.

Row spacing: The centerline-to-centerline distance in meters between rows of collectors, assuming that rows are laid out uniformly throughout the solar field.

Stow angle: The collector angle during the hour of stow. A stow angle of zero for a northern latitude is vertical facing east, and 180 degrees is vertical facing west.

Freeze protection temperature: The minimum temperature that the heat transfer fluid is allowed to reach in the field. The temperature ate which the freeze protection equipment is activated. SAM assumes that electric heat trace equipment maintains the fluid at the freeze protection temperature during the hours that freeze protection is operating.

Irradiation at design: The design point direct normal radiation value, used in solar multiple mode to calculate the aperture area required to drive the power cycle at its design capacity. Also used to calculate the design mass flow rate of the hear transfer fluid for header piping size.

Collector tilt: The angle of all collectors in the field in degrees from horizontal, where zero degrees is horizontal. A positive value tilts up the end of the array closest to the equator, a negative value tilts down the southern end. SAM assumes that the collectors are fixed at the tilt angle.

2.8.2 Uncertain variables

The financial parameters of the plant provide the model with the uncertainty factor and they are given below as per SAM. (SAM Manual, 2014)

Direct Capital Costs

- **Site Improvements ($\$/m^2$)** - A cost per square meter of solar field area to account for expenses related to site preparation and other equipment not included in the solar field cost category.

- **Solar Field ($/m^2)** - A cost per square meter of solar field area to account for expenses related to installation of the solar field, including labor and equipment.
- **HTF System ($/m^2)** - A cost per square meter of solar field area to account for expenses related to installation of the heat transfer fluid pumps and piping, including labor and equipment.
- **Storage ($/kWht)** - Cost per thermal megawatt-hour of storage capacity to account for expenses related to installation of the thermal storage system, including equipment and labor.
- **Power Plant ($/kWe)** - Cost per electric megawatt of power block gross capacity to account for the installation of the power block, including equipment and labor.

Indirect Capital Costs

- **EPC and Owner Costs** - EPC (engineer-procure-construct) and owner costs are associated with the design and construction of the project. Typical costs that may be appropriate to include in the EPC and Owner category are: Permitting, royalty payments, consulting, management or legal fees, geotechnical and environmental surveys, interconnection costs, spare parts inventories, commissioning costs, and the owner's engineering and project development activities.
- **Total Land Costs** - Costs associated with land purchases

Tax and Insurance Rates

- **Federal income tax rate**
- **State income tax rate**

- **Sales tax**
- **Insurance rate**

Analysis Parameters

- **Inflation Rate** – Annual rate of change of costs, typically based on a price index
- **Real Discount Rate** – A measure of the time value of money expressed as an annual rate.

2.9 Conclusion

SAM is a simulation software which allows users to simulate various technical and financial parameters for various renewable energy dependent power projects, for a particular location using specific weather data files from its own library, to make performance predictions and estimate the financial factors involved. It also has other features which enable the user to perform advanced analysis using optimization and sensitivity analysis. It is a simple and user-friendly software which helps facilitate decision making for people involved in the renewable energy industry. The decision variables and uncertain variables are decided using the parameters from SAM.

3 Introduction to BONUS algorithm

3.1 Stochastic optimization

The aim of an optimization problem is to calculate the value of the decision variable that optimizes the objective function within the given constraints. Stochastic optimization is a type of an optimization which deals with uncertainties. The objective function in a stochastic optimization problem is expressed in terms of some probabilistic representation (eg., expected value, variance, fractiles, most likely values). Along with the decision variables, it also has uncertain variables or parameters. A generalized stochastic optimization problem where the decision variables and uncertain parameters are separated, can then be viewed as:

$$\underset{x}{\text{Optimize}}\ Z = P_1(j\ (x, u))$$

subject to

$$P_2(h\ (x, u)) = 0$$

$$P_3(g(x, u) \geq 0) \geq \alpha$$

where u is the vector of uncertain parameters and P represents the cumulative distribution functional such as the expected value, mode, variance or fractiles.

Stochastic optimization problems can be further classified as stochastic linear programming, stochastic nonlinear programming and stochastic mixed integer linear and nonlinear programming problems. Our problem is a stochastic nonlinear programming problem; hence we will focus on that.

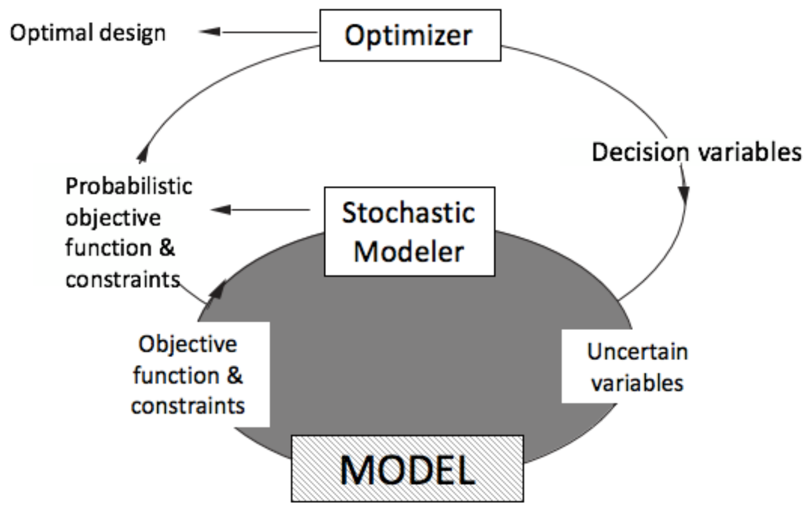


Figure 12. Pictorial representation of the stochastic programming framework

A generalized way of solving stochastic nonlinear programming problems is to use sampling based methods. A sampling loop can be embedded within the optimization model to capture the uncertainty for the decision variables. This can be computationally expensive as the model will have to re-run for each sampling point. Therefore, we consider efficient sampling techniques in the next section.

3.2 Sampling techniques

Sampling is a statistical procedure which involves selecting a limited number of observations, states or individuals from a population of interest. A sample is assumed to be the representative of the population to which it belongs to save time on evaluating the entire populations. It helps in inferring some knowledge about the population. The different types of sampling techniques are described below. The description of these techniques is derived from the sampling chapter by Diwekar and Ulas (2007).

3.2.1 Monte Carlo Sampling

This sampling technique was developed in 1949 by two scientists N. Metropolis and S. Ulam. Monte Carlo methods are numerical methods which provide approximate solutions by random sampling. In a crude Monte Carlo approach, a random value is drawn from the distribution provided by each input, and the corresponding output value is computed. (Metropolis and Ulam, 1949) The entire process is repeated a number of times to generate the number of output values wanted. These output values constitute a random sample from the probability distribution over the output induced by the probability distributions over the inputs.

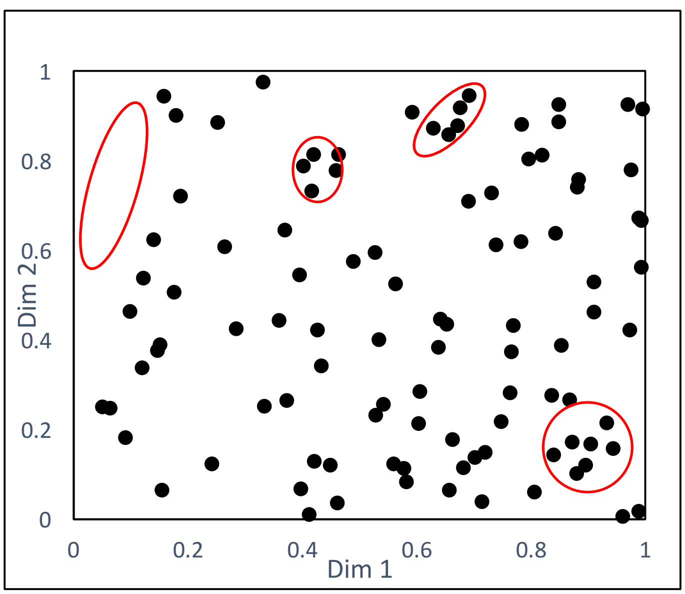


Figure 13. 100 two-dimensional sample points generated by Monte Carlo simulation

The disadvantage of Monte Carlo methods is that the samples generated are non-uniform in nature. As figure 3.2 shows, the samples are not uniformly distributed. Some regions have a cluster of samples and some regions are blank. Therefore, in order to reach higher accuracy, larger number of samples are required which affects the efficiency of this method.

3.2.2 Latin Hypercube Sampling

For increasing the efficiency of Monte Carlo simulations and overcome the disadvantages, variance reduction techniques have been developed (James, 1985). One of the most frequently used sampling approaches for variance reduction is Latin Hypercube Sampling (LHS). LHS can yield more precise estimates of the distribution function (McCay et al., 1979) and therefore reduce the number of samples required to improve computational efficiency. In this sampling the given distribution is divided in equiprobable zones and samples are drawn randomly from each equiprobable zone. The values drawn are paired randomly with other values of each uncertain parameter to complete the sampling. The main drawback of this stratification scheme in LHS is that it is uniform in one dimension and does not provide uniformity properties in multi-dimensions.

3.2.3 Hammersley Sequence Sampling

Hammersley Sequence Sampling (HSS) is an efficient sampling technique developed by Diwekar and coworkers (Diwekar and Kalagnanam, 1997; Kalagnanam and Diwekar, 1997; Subramanyan and Diwekar, 2006) based on quasi-random numbers. HSS uses Hammersley points to uniformly sample a unit hypercube and inverts these points over the joint cumulative probability distribution to provide a sample set for the variables of interest. This scheme ensures that the samples are more representative of the population showing uniformity properties in multi dimensions, unlike Monte

Carlo and Latin Hypercube Sampling.

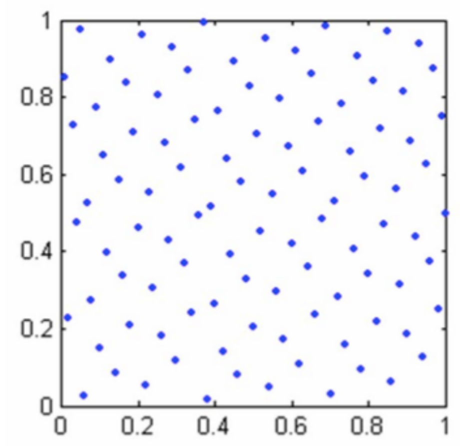


Figure 14. Generation of 100 Hammersley points in 2 dimension

3.3 Basics of BONUS

Better Optimization of Nonlinear Uncertain System (BONUS) algorithm was developed by Sahin and Diwekar in 2004. General techniques for these types of optimization problems (Figure 3.1) determine a statistical representation of the objective, such as maximum expected value or minimum variance. Once embedded in an optimization framework, the iterative loop structure emerges where decision variables are determined, a sample set based on these decision variables is generated, the model is evaluated for each of these sample points, and the value of the probabilistic objective and constraints are evaluated. The sheer number of model evaluations rises significantly causing this method ineffective for even moderately complex models. In the stochastic optimization iterations (Figure 3.1), decision variables values can vary between upper and lower bounds, and in sampling loop various probability distributions are assigned to uncertain variables. In the BONUS approach, initial uniform distributions (between upper and lower bounds) are assumed for decision variables. These uniform distributions together with specified probability distributions of uncertain variables form the base distributions for analysis. BONUS samples the solution space of the objective function at the beginning of the analysis by using the base distributions. As decision variables change, the underlying distributions for the objective function and constraints change, and the proposed algorithm estimates the objective function and constraints values based on the ratios of the probabilities for the current and the base distributions (a reweighting scheme), which are approximated using kernel density estimation techniques. Thus, BONUS avoids sample model runs in subsequent iterations. (Sahin and Diwekar, 2014)

3.4 Using BONUS for optimization

For using BONUS, the first step is to generate our base sample set. We have identified the 6 decision variables and 13 uncertain variables using SAM's physical parabolic trough model in the previous chapter. 2000 samples of these 19 variables are generated using HSS. Decision variables are assigned a uniform distribution with their upper and lower bounds specified. Normal distribution is assigned to the uncertain variables. The tables below show this information:

Parameter	Lower Bound	Upper Bound
Collector Tilt	0	7
Freeze Protection Temp.	120	180
Irradiation at Design	900	1200
Row Spacing	11	19
Solar Multiple	1	3

Stow Angle	150	170

Table 2. Decision variables and their bounds

Parameter	Mean (μ)	Std. dev. (σ)	Lower value (μ-3σ)	Upper value (μ+3σ)
HTF System Cost per metre square	50	1.65	45.05	54.95
Land Cost per acre	10,000	330	9010	10990
Power plant cost per Kwe	880	29.04	792.88	967.12
Site Improvement cost per metre square	20	0.66	18.02	21.98
Solar field cost per metre square	350	11.55	315.35	384.65
Storage system cost per kWht	70	2.31	63.07	76.93
EPC Costs % direct	15	0.495	13.515	16.485
Inflation Rate	2.5	0.0825	2.2525	2.7475

Real Discount Rate	5.5	0.1815	4.9555	6.0445
Federal income tax rate	28	0.924	25.228	30.772
Insurance rate	0.5	0.0165	0.4505	0.5495
Sales tax	5	0.165	4.505	5.495
State income tax rate	7	0.231	6.307	7.693

Table 3. Uncertain variables with mean, std. dev. and bounds

After generating the 2000 samples, we feed the samples in the BONUS interface. The results of using BONUS are discussed in the next chapter.

4 Results and Analysis

4.1 LCOE vs Iteration

Since, this is a non-convex problem, we have multiple local optimum solutions. From figure 15 we can see the optimums of 10 different solutions and how many iterations it took to achieve the optimal solution.

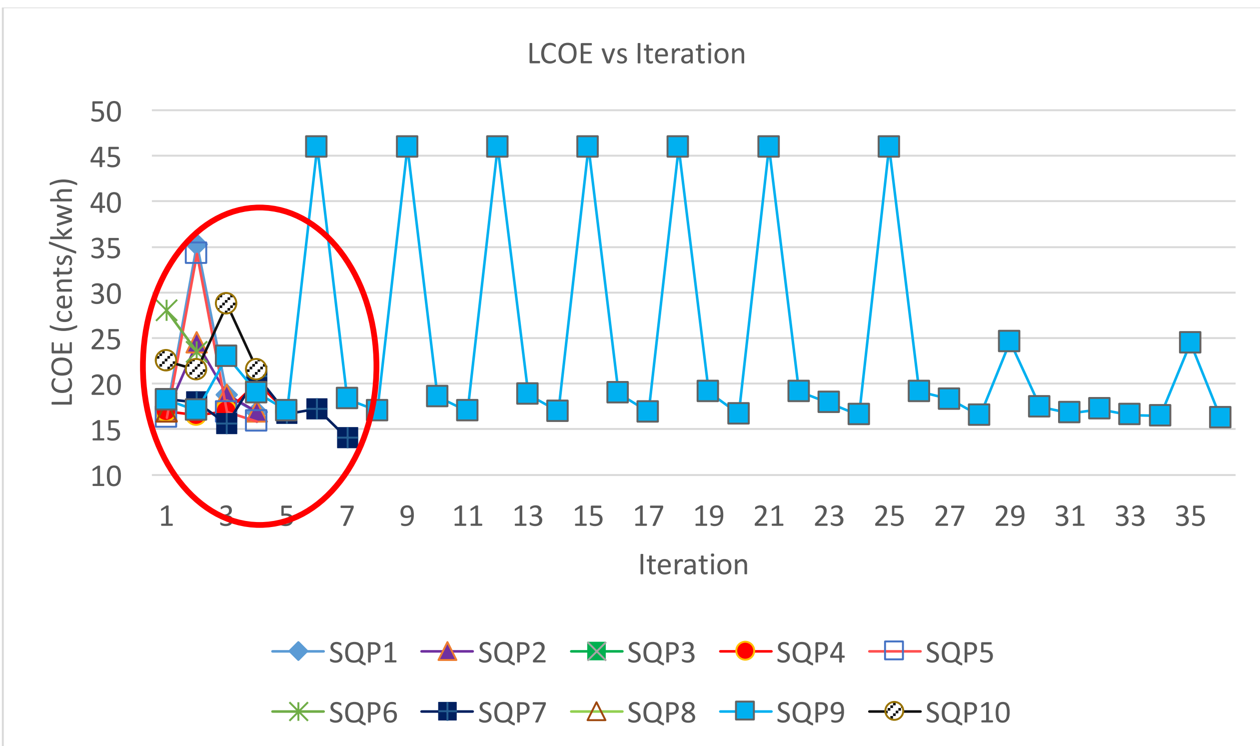


Figure 15. Graph showing no. of iterations required to achieve optimal solution for 100MW plant

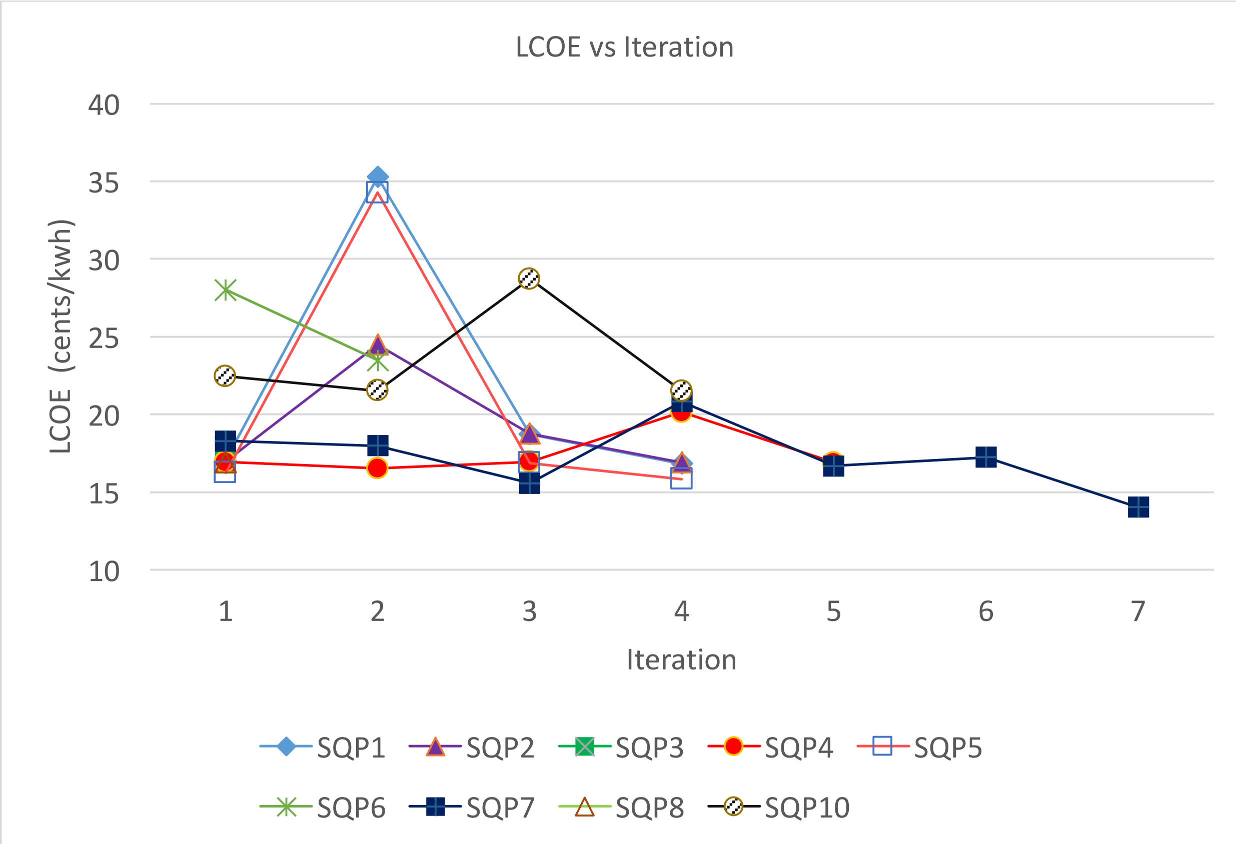


Figure 16. Zoomed in image of figure 15

Figure 16 gives us a clearer view of the graph. From both the charts we can see that the 7^{th} solution gives us the least value for LCOE out of all other optimums. That optimum is at 14.025 cents/kWh. It takes 7 iterations to get that optimum value. From BONUS, the values for the decision variables for that optimum are:

Collector tilt – 3.9171

Freeze protection temp - 155

Irradiation at design - 1025

Row spacing - 16.421

Solar multiple - 3

Stow angle – 165.03

To analyze our results more effectively we perform optimization for one more value of power capacity. We consider a larger capacity of 500 MW in our next optimization.

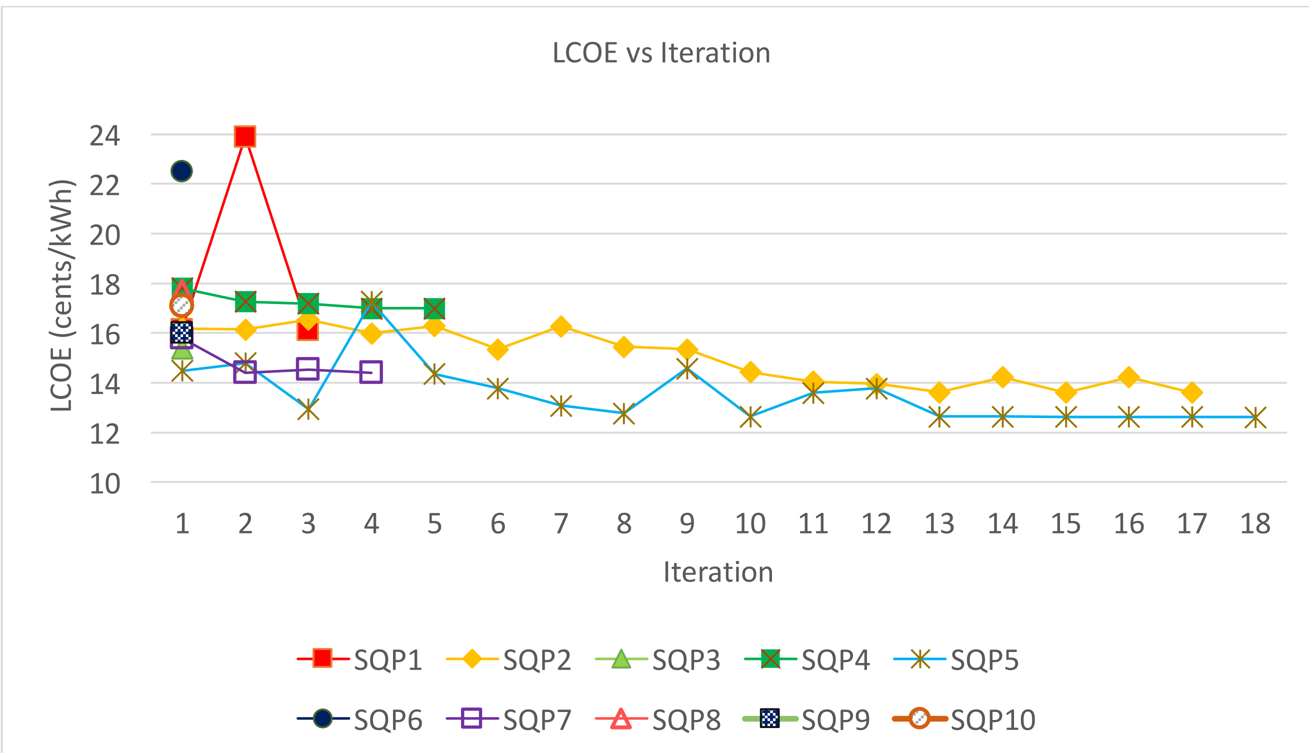


Figure 17. Graph showing no. of iterations required to achieve optimal solution for 500 MW plant

The graph again compares the number of iterations required to achieve the different optimums. The 5th solution gives us the lowest LCOE value of 12.623 cents/kWh taking 18 iterations to achieve that optimum value. The decision variable values for this optimum are:

Collector tilt – 5.5767

Freeze protection temp – 134.89

Irradiation at design - 1135

Row spacing – 13.155

Solar multiple – 2.6890

Stow angle – 162.99

To analyze the values of the decision variables, we compare them with the default or the base value of the decision variables

Decision variable	**Collector tilt (degrees)**	**Freeze protection temp (Celsius)**	**Irradiation at design (Watts/m^2)**	**Row spacing (m)**	**Solar multiple**	**Stow angle (degrees)**
Base	0	150	950	15	2	170
Optimal for 100 MW	3.9171	155	1025	16.421	3	165.03
Optimal for 500 MW	5.5767	134.89	1135	13.155	2.6890	162.99

Table 4. Analysis of decision variable values

4.2 CDF

To understand the effect of uncertainty further, we will compare the LCOE for the optimal and base values of decision variables using the parametric simulation feature on SAM.

We sample the uncertain variables using HSS again to generate 500 sample values for each variable. The samples have an underlying normal distribution. We simulate these 500 sample values for both sets of decision variables – base and optimal and then plot a CDF to compare the results. It is shown in figure 18.

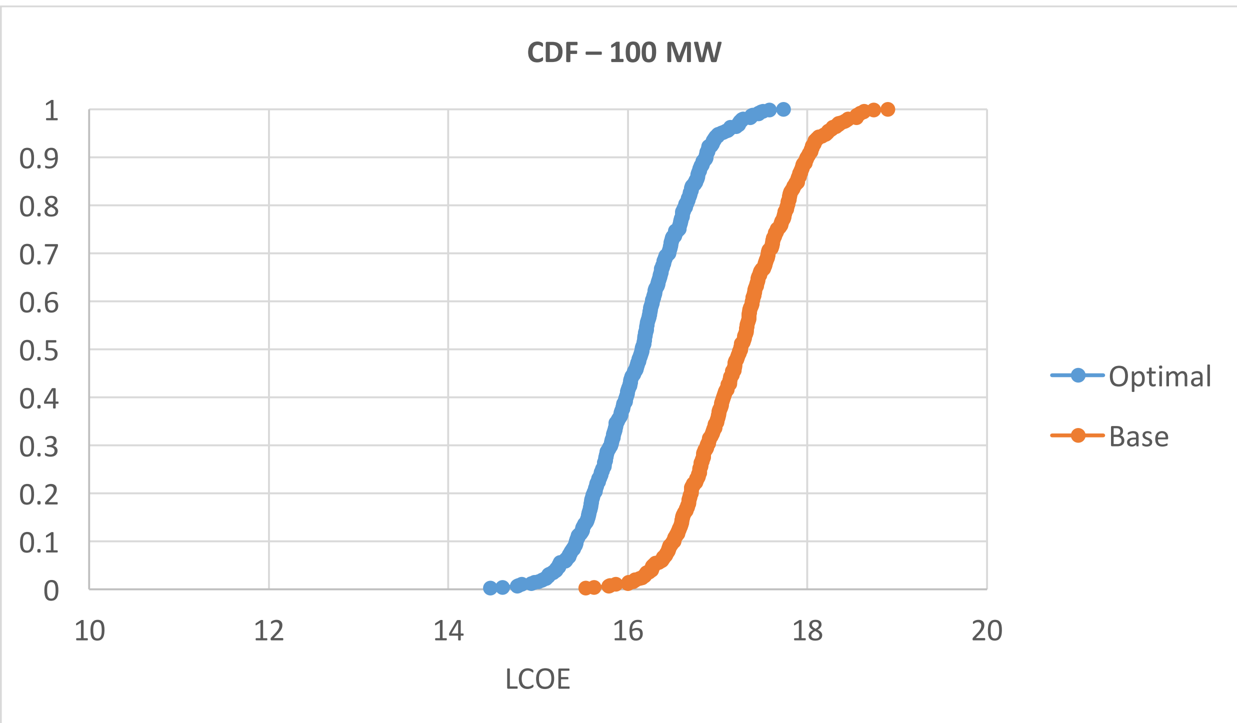


Figure 18. CDF plot of optimal values vs base values for 100MW plant

The mean for the optimal CDF is at 16.14 cents/kWh and the values range from 14.4712 cents/kWh to 17.7382 cents/kWh. The mean for the base CDF plot is at 17.245 cents/kWh and the values range from 15.531 cents/kWh to 18.8978 cents/kWh.

We repeat the same procedure for the 500 MW plant as well. The results are in figure 19.

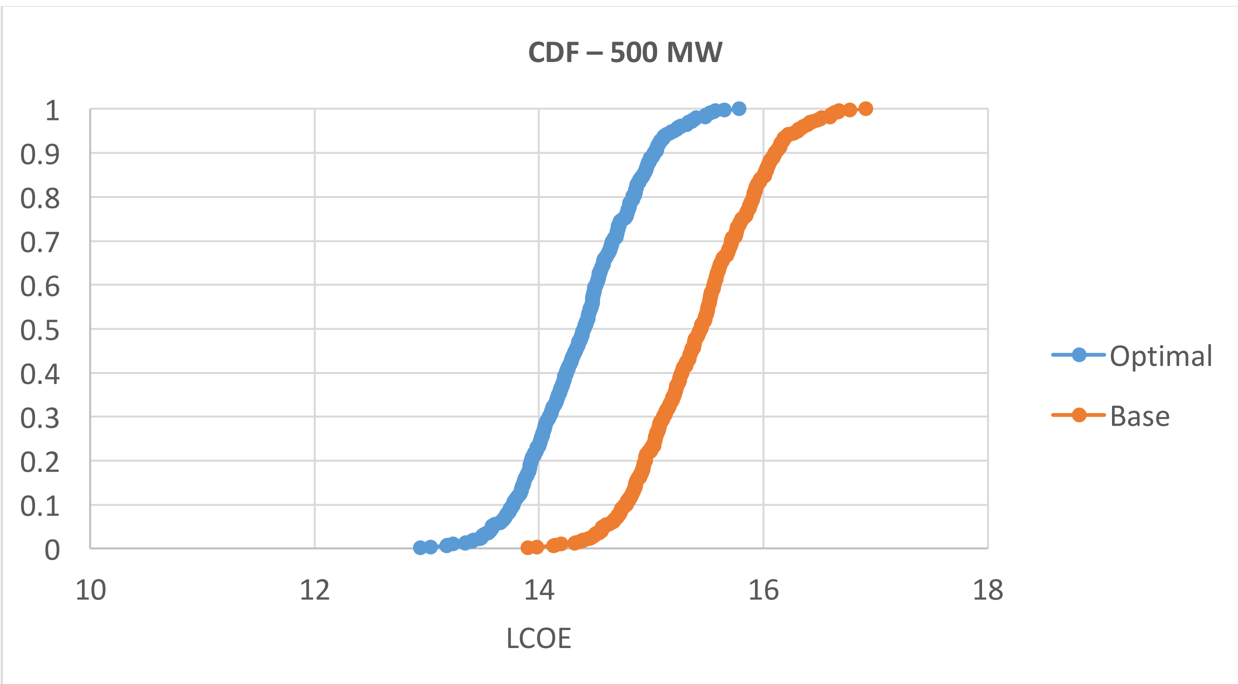


Figure 19. CDF plot of optimal values vs base values for 500MW plant

The mean for the optimal CDF is at 14.39 cents/kWh and the values range from 12.94 cents/kWh to 15.7845 cents/kWh. The mean for the base CDF is at 15.431 cents/kWh and the values range from 13.898 cents/kWh to 16.91 cents/kWh.

Both the CDFs show that there is a higher probability of getting a lower LCOE value using the optimal decision variables instead of the base decision variables.

We can also see the effect of uncertainty by comparing the deterministic and stochastic simulation values. Using both the sets of decision variables we simulate the model using SAM, to study the difference. As we can see, the stochastic results give us a lower value of LCOE compared to the deterministic results.

LCOE (cents/kWh)			
Base		Optimal	
Deterministic	**Stochastic**	**Deterministic**	**Stochastic**
17.25	17.2453634	16.15	16.142286
15.44	15.4316604	14.4	14.3910124

Table 5. Deterministic vs Stochastic simulation

4.3 Computational Efficiency

With BONUS, we also save on computational time since it requires less number of iterations to achieve the optimal solution. We can compute the reduction in computational time using the formula:

$$\textbf{Reduction in computational time} = \frac{\textbf{Difference in no.of iterations required}}{\textbf{Original no.of iterations}} \textbf{ x 100}$$

The total number of iterations required for optimizing the 100 MW plant is 68. Since there are 6 decision variables and 500 sample points, the original number of iterations required would be (6+1) x 500 x 68 = 238000. We simulated 2000 calculations using SAM. Hence, the difference in no. of iterations is 238000 – 2000 = 236000. Therefore, the reduction in computational time is

$$\text{Reduction in computational time} = \frac{236000}{238000} \text{ x } 100 = 99.15966\ \%$$

Performing the same calculation for the 500 MW plant. The total number of iterations required for optimization in the 500 MW plant is 52.

$$\text{Reduction in computational time} = \frac{(7x\ 500x\ 52)-2000}{(7\text{x}500\text{x}52)} \text{ x } 100$$

$$= 98.9011\ \%$$

4.4 Future Estimates

The U.S Energy Information Administration (EIA) have predicted the levelized cost of energy for different energy sources in 2020 (Annual Energy Outlook, 2015). The estimated LCOE for solar thermal technology in 2020 is 23.97 cents/kWh and for advanced coal technology is 11.57 cents/kWh. Our LCOE estimated for the 100 and 500 MW plants are 16.14 and 14.39 cents/kWh respectively. These estimates are calculated without including subsidies and tax incentives. If we include 30% federal tax credit in our simulations, we get 6.855 cents/kWh average LCOE for the 100 MW plant and 6.33 cents/kWh average LCOE for the 500 MW plant.

Note: The values for the other parameters in the simulation are given in the table below.

Parameter	**Value**
Deploy angle	10 deg.
No. of field subsections	12
Header pipe roughness	4.57e-005 m
HTF pump efficiency	0.85
Allow partial defocusing	Simultaneous
Field HTF fluid	Therminol VP-1
Design loop inlet temp.	293 degree Celsius
Design loop outlet temp.	391 degree Celsius
Min. single loop flow rate	1 kg/s
Max. single loop flow rate	12 kg/s
Header design min. flow velocity	12 m/s
Header design max. flow velocity	15 m/s
Collector azimuth	0 deg.
Water usage per wash	0.7 L/m^2,aper.
Washes per year	63
Hot piping thermal inertia	0.2 kWht/K-MWt
Cold piping thermal inertia	0.2 kWht/K-MWt
Field loop piping thermal inertia	4.5 Wht/K-m
Non-solar field land area multiplier	1.4
No. of SCA/HCE assemblies per loop	8

Collector name from library	Solargenix SGX-1
Reflective aperture area	470.3 m^2
Aperture width, total structure	5m
Length of collector assembly	100m
No. of modules per assembly	12
Average surface-to-focus path length	1.8m
Piping distance between assemblies	1m
Tracking error	0.994
General optical error	0.99
Geometry effects	0.98
Mirror reflectance	0.935
Dirt on mirror	0.95
Same values for all 4 collectors	
Receiver name from library	Schott PTR70 2008
Absorber tube inner diameter	0.066m
Absorber tube outer diameter	0.07m
Glass envelope inner diameter	0.115m
Glass envelope outer diameter	0.12m
Absorber flow plug diameter	0m
Internal surface roughness	4.5e-005
Absorber flow patter	Tube flow
Absorber material type	304L
Design gross output	111 MWe

Estimated gross to net conversion	0.9
Estimated net output at design (nameplate)	100 MWe
Rated cycle conversion efficiency	0.3774
Fossil backup boiler LHV efficiency	0.9
Aux heater outlet set temp.	391 degree Celsius
Fossil dispatch mode	Minimum backup level
Low resource standby period	2 hrs
Fraction of thermal power needed for standby	0.2
Power block startup time	0.5hr
Fraction of thermal power needed for startup	0.2
Minimum required startup temp.	300 degree Celsius
Max. turbine over design operation	1.05
Min turbine operation	0.25
Boiler operating pressure	100 bar
Steam cycle blowdown fraction	0.02
Turbine inlet pressure control	Fixed pressure
Condenser type	Evaporative
Ambient temp. at design	20 degree Celsius
ITD at design point	16 degree Celsius
Reference condenser water dT	10 degree Celsius
Approach temp.	5 degree Celsius
Min. condenser pressure	1.25 inHg
Cooling system part load levels	2

Full load hours of TES	6 hrs
Parallel tank pairs	1
Tank height	20m
Tank fluid min. height	1m
Tank loss coeff.	0.4 W/m^2-K
Cold tank heater set point	250 degree Celsius
Hot tank heater set point	365 degree Celsius
Tank heater capacity	25 MWht
Tank heater efficiency	0.98
Hot side HX approach temp.	5 degree Celsius
Initial TES fluid temp.	300 degree Celsius
Storage HTF fluid	Hitec Solar Salt
Piping thermal loss coeff.	0.45 W/m^2-K
Tracking power	125 W/sca
Required pumping power for HTF through power block	0.55 kJ/kg
Required pumping power for HTF through storage	0.15 kJ/kg
Fraction of rated gross power consumed at all times	0.0055
BOP parasitic value	0
Aux heater parasitic value	0.02273 MWe/MWcap
Fossil backup	0
Balance of plant	0
Contingency	10%
Sales tax basis	80

Fixed cost by capacity (O&M Costs)	20$/kW-yr
Degradation rate	0
Debt percent	100 %
Loan term	25 years
Loan rate	5% / year
Analysis period	25 years
Property tax assessed percentage	100% of installed cost
Annual decline	0
Property tax rate	0
Net salvage value	0
Depreciation – federal	5 yr MACRS
Depreciation – state	5 yr MACRS
Incentives	0
Metering	Single meter with monthly rollover credits in kWh
Year-end sell rate for net metering with kWh credits	0.02789 $/kWh
Fixed monthly charge	39.72$
Monthly minimum charge	0
Annual minimum charge	0
Electricity cost escalation rate	0% / yr
Demand minimum (Applicability)	400 kW

Table 6. Default values for SAM

5 Summary and Future Work

5.1 Summary

The parabolic trough technology was studied in detail. A better understanding of the various technical parameters related to the solar field, collectors, receivers involved in this technology, was developed. The major advantage of using the parabolic trough technology is that it is the most widely used and researched concentrating solar power technology compared to the other types.

Using SAM, the performance characteristics as well as the financial variables of the power plant were modeled. SAM helps in analyzing the decision variables and uncertain variables which have the maximum impact on the energy generated and the levelized cost of energy. The final results for the CDF plots were generated using the SAM Parametric simulation feature.

BONUS is an optimization algorithm which helped in reducing the levelized cost and saving on computational efficiency. It uses the concept of reweighting for estimating derivative information needed during optimization of nonlinear stochastic problems. Further, by selecting an efficient sampling technique like HSS, allowed for reduction in computational time as the repetitive nature of model evaluations is avoided.

Analyzing the results, we can see the reduction in LCOE values. The optimal values for the technical parameters were determined for a 100 MW plant as well as a 500 MW plant. Comparing the two different power capacities, we found out that 500 MW plant has a lower levelized cost than the 100 MW plant. Also, the difference between the deterministic and stochastic solutions showed the effect of uncertainty on optimization.

The reduction in computational time for this method of optimization was also calculated. Using the U.S. Energy department estimates, we compared our cost to the estimated cost of solar thermal and advanced coal technology in 2020.

5.2 Future work

Our model was based on San Diego, California. This same model can be replicated for studying different locations as the requirements and conditions for different cities will vary. Also the uncertainty associated with the weather data can be studied further and taken into consideration for this method of optimization.

The objective function for this optimization problem was to reduced the expected value of the levelized cost of energy. In the future, we could change the objective function to optimize the water requirements of the plant.

Using this same systematic method of optimization, we can use other concentrating solar power technologies to study the difference in savings.

References

1. Dey, C.J. (2004). "Heat transfer aspect of an elevated linear absorber". Solar Energy. 76 (2004): 243–249. doi:10.1016/j.solener.2003.08.030.
2. Jacobson, Mark Z.; Delucchi, M.A. (November 2009). "A Path to Sustainable Energy by 2030" (PDF). Scientific American 301 (5): 58–65. doi:10.1038/scientificamerican1109-58. PMID 19873905.
3. Jacobson, M. Z.; Delucchi, M. A. (2011). "Providing all global energy with wind, water, and solar power, Part I: Technologies, energy resources, quantities and areas of infrastructure, and materials". Energy Policy 39 (3): 1154. doi:10.1016/j.enpol.2010.11.040.
4. James B. A. P., 1985; Variance reduction techniques, J. Operations Research Society,36(6), 525.
5. Kalogirou, Soteris.; Lloyd, Stephen.; Ward John. “Modelling, optimisation and performance evaluation of a parabolic trough solar collector steam generation system.” Solar Energy Volume 60, Issue 1, January 1997, Pages 49–59. http://dx.doi.org/10.1016/S0038-092X(96)00131-4
6. McKay M. D., R. J. Beckman, and W. J. Conover, 1979; A Comparison of three methods of selecting values of input variables in the analysis of output from a computer code, Technometrics, 21(2), 239.
7. Moomaw, W., F. Yamba, M. Kamimoto, L. Maurice, J. Nyboer, K. Urama, T. Weir, 2011: Introduction. In IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner,

T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, C.von Stechow (eds)], Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

8. Pidaparthi, A.S; Prasad, N.R. "India's First Solar Thermal Parabolic Trough Pilot Power Plant." Energy Procedia Volume 49, 2014, Pages 1840–1847. http://dx.doi.org/10.1016/j.egypro.2014.03.195
9. Poullikkas, Andreas. "A Technology Selection Algorithm for Independent Power Producers." The Electricity Journal 02/2001; 14(6):80-84.
10. Poullikkas, Andreas. "Economic analysis of power generation from parabolic trough solar thermal plants for the Mediterranean region—A case study for the island of Cyprus." Renewable and Sustainable Energy Reviews Volume 13, Issue 9, December 2009, Pages 2474
11. Riffelmann, K.; Richert, T.; Nava, P.; Schweitzer, A. "Ultimate Trough® – A Significant Step towards Cost-competitive CSP." Energy Procedia Volume 49, 2014, Pages 1831–1839. http://dx.doi.org/10.1016/j.egypro.2014.03.194
12. Sahin, Kemal.; Diwekar, Urmila. "Better Optimization of Nonlinear Uncertain Systems (BONUS): A New Algorithm for Stochastic Programming Using Reweighting through Kernel Density Estimation." Annals of Operations Research November 2004, Volume 132, Issue 1, pp 47-68
13. Wang, Zhifeng. "Prospectives for China's solar thermal power technology development." Energy Volume 35, Issue 11, November 2010, Pages 4417–4420
14. http://instituteforenergyresearch.org/wp-content/uploads/2015/05/energy-consumption-mar-2015-printable.png
15. http://instituteforenergyresearch.org/wp-content/uploads/2015/07/Solar2-e1437773346871.png

16. http://www.schott.com/csp/english/parabolic-through-technology.html
17. http://www.renewables-made-in-germany.com/de/start/technologien/solarthermische-kraftwerke/solarthermische-kraftwerke/technologien-und-anwendungen.html
18. https://www.eia.gov/forecasts/aeo/electricity_generation.cfm
19. http://energy.gov/eere/energybasics/articles/linear-concentrator-system-basics-concentrating-solar-power
20. https://sam.nrel.gov/sites/sam.nrel.gov/files/content/documents/pdf/sam-help.pdf
21. "Electric Power Monthly 2/16" retrieved 2016-3-6
22. https://en.wikipedia.org/wiki/Renewable_energy_in_the_United_States
23. US Energy Information Administration,[2] 2016-3-8.
24. US Energy Information Administration, Electric Power Monthly, 2016-03-08.
25. "Electric Power Annual" [11] retrieved 2016-3-6
26. "Electric Power Monthly 2/16"[12] retrieved 2016-3-6
27. http://www.nrel.gov/docs/fy11osti/51825.pdf
28. http://www.seia.org/policy/solar-technology
29. https://en.wikipedia.org/wiki/Compact_linear_Fresnel_reflector#cite_note-Dey-1

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EDUCATION

University of Illinois — Chicago, Illinois

Master of Science in Industrial Engineering, GPA: 3.71/4.00 — May 2016

University of Mumbai — Mumbai, India

Bachelor of Engineering in Production Engineering, GPA: 3.48/4.00 — July 2014

WORK EXPERIENCE

UNIVERSITY OF ILLINOIS, Department of Bioengineering — Chicago, Illinois

Research Assistant — August 2015 – May 2016

- Thesis on stochastic optimization to reduce cost of energy in solar power plants
- Novel sampling techniques for uncertainty analysis
- New algorithmic framework for optimization under uncertainty

SIEMENS, Strategic Purchase & Logistics Department — Mumbai, India

Industrial Trainee — July 2013 - December 2013

- Designed scheduling and networking model to reduce total cost by 35% for manufacturing motor components
- Expedited operations and manufacturing processes at the supplier's end to reduce time by 48%

PROJECTS

Linear programming model for optimization, University of Illinois — December 2014

- Collected data of performance statistics of each squad player representing their respective team
- Generated an algorithm using the concepts of mixed integer linear programming and applied it on MATLAB and Excel to yield the optimal team with maximum points within the fixed budget constraint

Managing a Global Supply Chain, University of Illinois — December 2014

- Conducted an in-depth analysis of Apple's supply chain and estimated their future performance to decide whether or not an analyst's firm should continue holding their shares
- Forecasted Apple's 5 year sales using time series forecasting models on Minitab and Excel

LEADERSHIP AND ACTIVITIES

DJS Racing, Formula SAE Team — January 2012 - August 2014

- Participated as member of team in developing a Formula-style race car for Formula Student Germany

Intramural Official, University of Illinois — August 2015 – May 2016

- Officiated soccer, volleyball, cricket, basketball matches for intramurals with over 500 participants