OPTIMIZATION OF STORED ENERGY DISPATCH FOR
CONCENTRATING SOLAR POWER SYSTEMS

by
Michael J. Wagner
A thesis submitted to the Faculty and the Board of Trustees of the Colorado School of Mines in partial fulfillment of the requirements for the degree of Doctor of Philosophy (Mechanical Engineering).

Golden, Colorado
Date ________________

Signed: __________________________
       Michael J. Wagner

Signed: __________________________
       Dr. Robert Braun
       Thesis Advisor

Signed: __________________________
       Dr. Alexandra Newman
       Thesis Advisor

Golden, Colorado
Date ________________

Signed: __________________________
       Dr. Greg Jackson
       Professor and Head
       Department of Mechanical Engineering
ABSTRACT

Concentrating solar power (CSP) is an emerging technology capable of generating renewable, dispatchable power using cost-effective thermal energy storage. Dispatchability imparts significant value to a power generation technology, both expanding the applications in which it is useful and – perhaps more critically – enabling the proliferation of other non-dispatchable renewable technologies by supplementing their performance during transient periods of low or variable production.

Current CSP technology is functional but sub-optimal, especially with regard to solar field design and to strategies for optimally dispatching power. A comprehensive, immediate, and systematic optimization approach is needed to drive down technology costs, thus improving the competitive position of CSP in the marketplace. Several tools are a necessary part of this process, including those for solar field design and optical characterization, plant productivity simulation, optimal operations scheduling (i.e., dispatch optimization), cost assessment, and financial performance evaluation. However, advancement in each critical area has been uneven to-date, with solar field design and optical characterization and dispatch optimization less established than other areas. Herein lies the challenge undertaken in this thesis – namely, to identify mathematical models and computational techniques that advance these two aspects of CSP technology development.

We present methods for improved solar field design, characterization, and optimization that advance previous work by extending an existing technique for analytical flux modeling to individual heliostat reflections, enabling rapid computational prototyping of a broader range of field designs. Once defined, a plant’s dispatch schedule can be optimized to maximize revenue from electricity sales, minimize costs due to subsystem start-up or change in production, and enforce contractual or technological constraints. We undertake this task by formulating a mixed-integer linear program that more realistically and accurately accounts
for a variety of operational modes and subsystem performance characteristics. The advances in field design and characterization and in dispatch optimization are adopted by an industry-leading project developer who demonstrates through simulation the viability of CSP molten salt tower technology as a dispatchable resource, where previous work had left in question the impact of optimized dispatch.
# TABLE OF CONTENTS

ABSTRACT ................................................................. iii

LIST OF FIGURES ......................................................... ix

LIST OF TABLES ........................................................... xii

LIST OF ABBREVIATIONS ................................................... xiii

ACKNOWLEDGMENTS ....................................................... xiv

DEDICATION ............................................................... xvi

CHAPTER 1 INTRODUCTION ............................................... 1

1.1 Technology Background .............................................. 4

1.2 Solar Field Design and Characterization ............................ 8

1.3 Dispatch Optimization ............................................... 9

1.4 Modeling Tools and Resources ..................................... 11

1.5 Literature Review .................................................. 14

1.5.1 Summary of Content ............................................ 17

CHAPTER 2 SOLARPILOT: A POWER TOWER SOLAR FIELD LAYOUT AND CHARACTERIZATION TOOL ........................................ 19

2.1 Abstract ............................................................ 19

2.2 Introduction .......................................................... 20

2.2.1 Modeling approaches ......................................... 21

2.3 Tool description .................................................... 23

2.3.1 Analytical methods ............................................. 24
5.2 Dispatch Optimization .............................................. 114
5.3 Application ......................................................... 116
5.4 Future and Recommended Work .................................. 117
  5.4.1 Dispatch subject to uncertainty .............................. 117
  5.4.2 System optimization ......................................... 118
  5.4.3 Application to other technologies .......................... 119

REFERENCES CITED .................................................. 120
## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>The typical project analysis process in which the goal is to assess the techno-economic performance of a particular system configuration. Boxes shaded blue represent existing models or tools, and green boxes represent work undertaken in this thesis.</td>
</tr>
<tr>
<td>1.2</td>
<td>A molten salt power tower. (Image credit SolarReserve).</td>
</tr>
<tr>
<td>1.3</td>
<td>SolarReserve’s <em>Crescent Dunes</em> facility.</td>
</tr>
<tr>
<td>1.4</td>
<td>Technology summary</td>
</tr>
<tr>
<td>1.5</td>
<td>Layout and flux results for identically defined systems in which heliostats are focused (a,c,e) and flat (b,d,f). Flux intensity is shown on the receiver surface, and the aimpoint plot shows position of the point on the receiver, relative number of heliostats (dot size), and average distance of heliostats (dot color) for each aim point.</td>
</tr>
<tr>
<td>1.6</td>
<td>The logical dispatch control for TES presented by Guédez et al. (2015) (reproduced with permission).</td>
</tr>
<tr>
<td>2.1</td>
<td>SolarPILOT graphical interface showing a selected region of the heliostat field after an afternoon simulation with shadowing efficiency data overlay.</td>
</tr>
<tr>
<td>2.2</td>
<td>Intercept factor of a $4 \times 4$m heliostat on a $10 \times 10$m receiver as a function of radial distance. The heliostat focal length is 100m and total optical error is 5 mrad.</td>
</tr>
<tr>
<td>2.3</td>
<td>Optical intercept grouping mesh for a north-facing receiver. Each element corresponds to a maximum variation of 5% optical intercept factor.</td>
</tr>
<tr>
<td>2.4</td>
<td>The impact of dynamic grouping on field layout and annual energy production.</td>
</tr>
<tr>
<td>2.5</td>
<td>The impact of the number of days and hourly simulation frequency used during field layout on layout dislocations (top) and annual energy error (bottom) as simulated in SAM. The cases shown are relative to a layout in using 50 days at two-hour frequency.</td>
</tr>
</tbody>
</table>
Figure 2.6 Land-restricted layout with land boundaries overlaid in the top right corner. The available land area is defined by a single inclusion area and two exclusion regions.

Figure 2.7 Heliostat image on the receiver plane in three position scenarios. Bounding-box image extents are shown for each case, indicating the dependence of “scaled receiver” size on the heliostat’s receiver view.

Figure 2.8 Illustration of the impact of quadrature scaling on the heliostat field layout.

Figure 2.9 The difference in calculated optical efficiency between DELSOL3 and SolarPILOT as a function of sun position for the case shown in Table 2.1. The difference shown is DELSOL fractional efficiency minus SolarPILOT fractional efficiency at each evaluated sun position.

Figure 3.1 Molten Salt Power Tower system configuration that is modeled in SAM. The system consists of a heliostat field, molten salt receiver, direct TES system, steam generation system, Rankine power cycle, and heat rejection system. (Graphic ©NREL/Al Hicks)

Figure 3.2 Cycle efficiency as a function of input thermal power represented using a piece-wise linear function.

Figure 3.3 The impact of time horizon length (hours) on annual energy production and PPA price.

Figure 3.4 Information flow in the SAM-MSPT model. The MIP formulation is solved as a simultaneous set of equalities and inequalities, and the hourly solution profile is used by the CSP Controller to set target power production levels and operational states over the subsequent operational time horizon.

Figure 3.5 Market pricing scenarios presented by Guédez et al. These tariff schedules are implemented to determine the impact of dispatch optimization on system sizing.

Figure 3.6 Comparison of performance profiles for the pool price tariff schedule. Plots (a) and (b) show traces of the TES charge state for each day of the year. Plots (c) and (d) show box-whisker plots of daily electricity production variability over a year grouped by hour of the day. Each box indicates the mean annual electricity generation by hour, the first and third quartile limits (box limits), and two times the interquartile range (whiskers). “Outliers” are shown as blue dots. Summer (red) and winter (blue) tariff multipliers are overlaid on each plot.
Figure 3.7  Plant power generation profile with varying change in production penalty values, $C_{δW}$. (Penalties are given in the legend.)  ........................................ 74

Figure 3.8  Impact of production change cost penalty on number of turbine cycles per day, annual energy generation, and PPA price for two pricing scenarios – a generic summer afternoon peak schedule (Default) and a morning/evening double-peak (Peaker) schedule. Annual energy and PPA price are shown as fractional values relative to the lowest-penalty case. ......................................................... 77

Figure 3.9  Number of cycle starts per year, annual energy output, and PPA price for the Default case with varying scenarios for cycle start-up cost. ............................. 78

Figure 4.1  A molten salt power tower. (Image credit SolarReserve) .......................................................... 82

Figure 4.2  SolarReserve’s Crescent Dunes facility. .......................................................... 83

Figure 4.3  Information flow in the SAM-MSPT model. Work presented in this paper focuses on the Production Forecast, MIP Formulation, and MIP solver. .......................................................... 94

Figure 4.4  Heliostat field layout for Rice as generated by SolarPILOT. .................................................. 96

Figure 4.5  Market pricing scenario. The annual pricing profile (top) and a selection from March overlaid with irradiance data (bottom) are shown. ........................................ 97

Figure 4.6  Electricity generation schedules from the SAM (black) and production scheduler (orange) simulations over a time period of May 17th-22nd. The electricity price multiplier is also shown. .................................................. 99

Figure 4.7  Comparison of expected revenue using the production scheduler algorithm (horizontal axis) and SAM (vertical axis) as aggregated over three time horizons – daily, weekly, and monthly. Revenue from sales is shown on the top, and net revenue including costs is shown on the bottom. The line of perfect agreement is shown in each case. Note that the left and center plot axes are logarithmic. .................................................. 100

Figure 4.8  Fraction of a capacity payment gained by SAM and production scheduler (bottom left) and by the heuristic (bottom right) as a function of the number of top-priced hours that are subject to capacity incentives, with the price multiplier duration curve shown (top). .................................................. 101
LIST OF TABLES

Table 1.1 Definition of modeling terminology .................................. 3
Table 2.1 Parameters for the comparison case study and simulation results. 43
Table 3.1 Parameters and sets used in $\mathcal{R}$. ................................. 55
Table 3.2 Variables used in $\mathcal{R}$. ...................................................... 57
Table 3.3 Case study plant design and control parameters ....................... 70
Table 3.4 Characteristics for each market scenario in which PPA price is at a minimum value, both for heuristic (H) and optimized (O) dispatch. 72
Table 4.1 Case study plant design and control parameters. ..................... 95
Table 4.2 Metrics of interest and relative improvement of SAM over the original heuristic approach and production scheduler. .................. 98
**LIST OF ABBREVIATIONS**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>API</td>
<td>application programming interface</td>
</tr>
<tr>
<td>CAISO</td>
<td>California Independent System Operator</td>
</tr>
<tr>
<td>CSP</td>
<td>concentrating solar power</td>
</tr>
<tr>
<td>DOE</td>
<td>Department of Energy</td>
</tr>
<tr>
<td>HTF</td>
<td>heat transfer fluid</td>
</tr>
<tr>
<td>LCOE</td>
<td>levelized cost of energy</td>
</tr>
<tr>
<td>MCRT</td>
<td>Monte-Carlo ray-tracing</td>
</tr>
<tr>
<td>MIP</td>
<td>mixed integer linear problem</td>
</tr>
<tr>
<td>MIQP</td>
<td>mixed integer quadratic problem</td>
</tr>
<tr>
<td>NREL</td>
<td>National Renewable Energy Laboratory</td>
</tr>
<tr>
<td>O&amp;M</td>
<td>operations and maintenance</td>
</tr>
<tr>
<td>PPA</td>
<td>power purchase agreement</td>
</tr>
<tr>
<td>PS</td>
<td>Production Scheduler</td>
</tr>
<tr>
<td>PV</td>
<td>photovoltaic</td>
</tr>
<tr>
<td>SAM</td>
<td>System Advisor Model</td>
</tr>
<tr>
<td>SAM-MSPT</td>
<td>SAM Molten Salt Power Tower</td>
</tr>
<tr>
<td>SolarPILOT™</td>
<td>Solar Power tower Integrated Layout and Optimization Tool</td>
</tr>
<tr>
<td>TES</td>
<td>thermal energy storage</td>
</tr>
<tr>
<td>TOD</td>
<td>time-of-dispatch</td>
</tr>
</tbody>
</table>
ACKNOWLEDGMENTS

I foremost gratefully acknowledge the contributions, guidance, and collective wisdom of my advisors Professors Alexandra Newman and Rob Braun. Thank you for investing your time and energy in my education and research, for your enthusiasm and vision (respectively), and for your flexibility; I hope that I can return more than a fraction of what you’ve given me. I also thank Professors Aaron Porter and Jason Porter at Colorado School of Mines, Provost Terry Parker at Florida Polytechnic University, and Dr. Sven Leyffer at Argonne National Laboratory for your generosity and feedback as part of my thesis committee.

I owe a debt of gratitude to my colleagues at NREL who supported and enabled my studies at Colorado School of Mines, especially Mark Mehos who offered me more flexibility and resources than I would have offered myself. I am certain that I would not have persevered should I not have had the good fortune of working for you. I also thank Chuck Kutscher for encouraging me to take on this endeavor and serving as a template for how to do so.

Aid in development of content was received from several colleagues, including through prior work on models and methodologies. I acknowledge Tim Wendelin of NREL as the author of SolTrace for consultation in implementing his software in SolarPILOT and for discussing methods for computational efficiency improvement, Janna Martinek of NREL for contributions to the dispatch optimization model including constraint modification and algorithm testing, Ty Neises of NREL for development of the simulation control algorithm and for generally making the work that I do much easier and more enjoyable, and Aaron Dobos and Steve Janzou of NREL who pioneered the SAM interface development and accommodated my many feature requests.

I furthermore gratefully acknowledge Will Hamilton and Jennifer DiCarlo at Colorado School of Mines for their contributions to the MIP mathematical formulation, and Charles Diep, Jolyon Dent, and Adam Green at SolarReserve® for feedback on modeling priorities
and plant operations.

Portions of this work were funded by the U.S. Department of Energy office of Energy Efficiency and Renewable Energy under NREL Contract No. DE-AC36-08GO28308, and award numbers DE-EE00025831 and DE-EE00030338. The dedicated project managers who oversee this work deserve thanks, especially Mark Lausten and Avi Schulz; I appreciate your personal interest and willingness to accommodate an engineer who happened also to be an aspiring student.

Much of this work was inspired by and can be traced back to my Master’s degree advisors at the University of Wisconsin–Madison, namely Professor Emeritus Sandy Klein and Professor Doug Reindl. Despite having no tangible involvement in this research, it was fundamentally shaped and undoubtedly improved by my time with you the Solar Energy Lab.

Finally, I thank my family for their unending support, curiosity, and love. To my mom and grandmother, thank you for pushing me to test my limits, and to my dad, thank you for showing me that self realization is only meaningful within the context of those that you love. To my late grandfathers and grandmother, I hope my accomplishments honor the memory of your remarkable lives, and that others can see you living on in me. To my brothers and sisters Nathan, Emily, David, Johanna, Brian, and their spouses and families, you all shaped who I am – in your own ways – more than anyone else, and I am so proud of who we are. To my extended family – Patrick, Tami, Chad, and Tracie, thanks for providing me with a much-needed respite from the tedium of graduate work.

* * *

To my wife Katie and my son Charlie, you have sacrificed so much to help me to follow this dream, and the achievement is ours. You stand alone in my life and have my gratitude first, last, and always. Because of you, I’ve learned that a volume of words has less power than time.
For Katie and Charles,
without whom life would be dull –
let’s make up lost time.
Concentrating solar power (CSP) systems are poised to become an essential contributor to global renewable energy production, as CSP with thermal energy storage (TES) provides cost-effective flexibility in meeting electricity demand. By serving as a dispatchable renewable resource, CSP ultimately enables significantly greater market penetration from other variable renewables such as wind and solar photovoltaic (PV) systems [1]. However, realization of CSP’s potential value requires effective methods for identifying and executing electricity generation (hereafter referred to as “dispatch”) profiles that account for the timing and magnitude of thermal power collection, the energetic state of thermal storage over time, the thermodynamic and thermal efficiencies of system processes, and the price at which electricity may be sold, all of which vary with time.

CSP is a capital-intensive and relatively complex source of power, and each subsystem must be efficiently utilized to minimize the price at which the technology is competitive with other generators. This requires proactive modeling and predictive simulation during both the design and operations phases of a project, and robust and accurate methods are needed to determine solar field layout, expected performance, plant behavior, and optimal dispatch strategies. Existing tools such as the National Renewable Energy Laboratory (NREL)’s System Advisor Model (SAM) [2] and the German Aerospace Center’s Greenius [3] (among others [4]) are capable of simulating the performance of CSP systems over some time horizon of interest – typically one year at hourly intervals – thus disposing of the challenge of heat transfer and thermodynamic analysis. However, relatively few publicly available options exist for solar field design, optical characterization, and dispatch optimization, leaving deficiencies in the CSP technology development process.
Figure 1.1 illustrates the design and simulation processes, beginning with sizing of the TES, solar field, and power cycle subsystems along with component operations and performance parameters. Next, the solar field design is generated whereby heliostat positions, receiver and tower dimensions, and optical design parameters are produced. Once a field has been defined, it is optically characterized over a range of possible sun positions, and the optical efficiency and receiver flux boundary conditions are passed to the system simulation which determines detailed plant performance over time. Decisions within the simulation regarding when electricity should be generated can be made either using heuristic algorithms that enforce operating modes based on a set of rules regarding the current and previous state of the plant subsystems or with an optimized dispatch profile which requires expected performance and pricing information. The expected performance of the system is determined using physics-based models which include calculation of heat transfer rates, temperatures, and thermodynamic properties within the system, and the results of the simulation are used along with a cost model to assess project financial performance. Depending on the outcome, the process may be repeated with different plant sizing or component specifications to improve financial return. This thesis undertakes research and development of solar field design and characterization as well as dispatch optimization methods with an overarching goal of accelerating the CSP technology design process.

The sections that follow within Chapter 1 provide additional technology background and introduce the topics of solar field design and dispatch optimization, and review engineering models and simulation tools upon which the current research is built. Finally, a brief recapitulation of related work is provided, though more detailed analysis is given in Chapters 2 through 4, as needed.

A Note on Terminology
This work utilizes methods from engineering, software development, operations research, and applied math disciplines in which familiar terms related to modeling are often employed in different and incompatible ways. This can confuse the meaning of the concepts in this doc-
Figure 1.1: The typical project analysis process in which the goal is to assess the techno-economic performance of a particular system configuration. Boxes shaded blue represent existing models or tools, and green boxes represent work undertaken in this thesis.

To provide clarity, we define our usage of several common terms in this document. These definitions are not necessarily formal, but represent intended usage.

Table 1.1: Definition of modeling terminology

<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>algorithm</td>
<td>A repeatable procedure that takes a set of input information and returns a value (or values) of interest. Often used interchangeably with calculator. From software development.</td>
</tr>
<tr>
<td>calculator</td>
<td>Often used interchangeably with algorithm. More specifically, it can be a subset of equations or steps in evaluation of a metric of interest that are mathematically distinct from (i.e., not solved simultaneously with) other equations or evaluation steps in a model.</td>
</tr>
<tr>
<td>formulation</td>
<td>A set of expressions that mathematically describe the behavior of a system. This term describes the formal set of mathematical expressions used in the plant dispatch optimization study. A formulation is a specific type of model. From operations research.</td>
</tr>
<tr>
<td>constraints</td>
<td>Mathematical expressions that restrict the values that a variable can assume as a function of fixed parameters or other variables. From applied math.</td>
</tr>
</tbody>
</table>
model A mathematical representation of a process or system of interest. Models may account for spatial and/or time dependence of a process or system. This term is often vague because of its generality, as it forms a superset of various other terms. It can be used instead of algorithm, calculator, simulation, and tool, though not interchangeably. From engineering and software development.

objective An expression that quantifies an optimization goal. From operations research.

optimization The process of systematically manipulating variable values to improve the objective function value to an extremum. Primarily from operations research.

parameter A fixed quantity in a model; in opposition to variable. From operations research. Sometimes contradicts engineering usage; e.g., a “parameterization study” in which the goal is to determine the best parameter values for a model.

simulation Characterization of a system by calculating its state over time. Simulation assumes time dependence of a system or process, and it typically requires modeling the response of a system or process to varying input over a finite time series. From engineering.

software A package that combines an interface for specifying parameters and retrieving results with one or more models. Often used in combination with other terms from this list (e.g., simulation software – software whose purpose is the configuration and execution of a simulation). From engineering and software development.

variable A quantity whose value can be changed to achieve a desired outcome, as opposed to a parameter. From operations research.

1.1 Technology Background

CSP technologies can utilize heat from concentrated sunlight from a field of tracking mirrors to generate electricity, reform fuel, provide process heat, or augment fossil plant heat sources. Among the four major CSP technologies – Parabolic Trough, Linear Fresnel, Dish Stirling, and Power Tower – the lattermost (also called a “Central Receiver” system and illustrated in Figure 1.2) has greatest potential for efficiency improvement and cost reduction [5] due to its flexible configuration and high solar flux concentration ratios. The first US commercial power tower facilities are only recently coming online with BrightSourceTM’s Ivanpah I-III facilities and SolarReserveTM’s Crescent Dunes facility (see Figure 1.3). These
facilities mark an important step for CSP in the US, but the relative scarcity of power tower facilities worldwide has left a dearth of knowledge on operations and maintenance (O&M) costs, performance impacts, and operating strategies to minimize cost of energy.

![Figure 1.2: A molten salt power tower. (Image credit SolarReserve).](image)

Current CSP cost-of-energy is competitive in some markets, capable of bidding at an estimated 13¢/kWh for molten salt power towers without tax incentives [6], but the cost of energy must continue to decrease for CSP to achieve broad adoption. The United States Department of Energy (DOE) has developed the SunShot program to aggressively seek cost-of-energy reduction in both CSP and PV technologies. In CSP, research is focused on simultaneous reduction of component costs and performance improvement in each plant subsystem. Power tower technologies enjoy several key advantages over renewable and fossil alternatives, but certain challenges must be addressed to accelerate widespread commercial deployment, as summarized in Figure 1.4.

Electricity-generating power tower systems use concentrated light to warm a heat transfer fluid (HTF) which is typically a molten nitrate salt. The HTF is then sent to a power
generation cycle or diverted into TES for later use. Power tower systems are capable of producing electricity in the majority of hours throughout the year (in fractional terms, this is the capacity factor) to the point of approaching base-load status [9]. However, US market structures often preferentially value energy production during peak demand hours of the day. Hence, cost-effective solutions typically operate diurnally with potential for multiple, daily production cycles. Cycle startup and grid synchronization typically require between one and three hours, depending on the extent to which equipment has cooled during down-time. Equipment manufacturers limit the startup rate because the lifetime of power generation equipment is highly sensitive to heating and cooling rates.

Thermal storage is – in principle – a straightforward proposition. Heated media is stored in an insulated tank system and dispatched on demand to heat the power cycle working fluid to generate electricity. However, optimal utilization of a TES resource is complex and
Technology advantages and commercialization challenges

- Employs thermal energy storage whereby heat transfer media (typically, a fluid) energized by concentrated solar flux can be stored in an insulated high-temperature tank system with round-trip efficiency of >99% [7]
- Dispatches on demand using thermal storage, providing reliable power at night, during cloudy periods, or during hours with excess demand
- Achieves higher concentration ratios, working temperature, and conversion efficiency than other CSP technologies
- Not a significant emitter of greenhouse gases

- Subject to variable resource availability and forecast uncertainty
- Rather than operating as a baseload plant, the most cost-effective solutions require diurnal thermal cycling as the plant starts and ends operation as needed
- Frequent cycling increases the frequency of required power block maintenance and incurs startup delays [8]
- System design and performance prediction require relatively complex engineering software

Figure 1.4: Technology summary

multi-faceted: thermal energy may be dispatched to produce electricity immediately upon first availability, or thermal energy may be reserved for next-day peak periods at risk of filling storage and dumping energy, or a portion of the thermal energy can be reserved to maintain equipment temperatures, reducing power cycle startup time, etc. Many possible dispatch permutations can emphasize producing peak power, operating through transients, expediting daily startup, etc., in different ways. The best operation strategy can change day-to-day throughout the year, depending on the weather and market pricing forecasts. CSP systems – though having a significant operational advantage due to TES – must also utilize tools that respond to energy production uncertainty in the short term (24-72 hours).

Previous work has shown that careful energy system design and dispatch can reduce costs, e.g., for an appropriately retrofitted building, relative to reliance solely on the grid [10]. Rather than performing an expensive retrofit, a more cost-effective and, indeed, imperative, approach given current market competition for low-cost energy production systems calls for an immediate, structured optimization effort regarding CSP.
1.2 Solar Field Design and Characterization

The goal of solar field design is to identify a heliostat field and receiver system that generates thermal energy over the year in the most cost-effective manner while meeting thermal rating requirements and operational constraints. The design process begins with specification of receiver and tower geometry values, heliostat dimensions and optical parameters, spacing and layout factors, and other conditions. A number of potential heliostat positions are enumerated based on this geometry, and each position is evaluated over a range of sun positions to estimate annual power delivery. The most productive heliostats are selected from those available until the power output at the reference (design-point) condition is met, and the remainder are discarded. Once a layout has been identified, the optical performance of the system is characterized by calculating the intensity and spatial distribution of the reflected flux from each heliostat on the surface of the receiver. If all heliostats are aimed such that the reflection targets a single point or centerline on the receiver, the flux intensity is often too high, and material failure will result. Instead, heliostat aiming schemes are applied to “spread out” the flux across the receiver, ensuring peak flux limits are observed but minimizing losses from flux spilling off of the absorbing surface. The aiming and flux intensity calculations are repeated over a range of representative sun positions to produce lookup tables describing total solar field optical efficiency and the flux distribution on the receiver, and this information is used during an hourly-annual performance simulation.

This process can be computationally burdensome, though speed improvements might be identified with some effort. Work presented in Chapter 2 outlines the field design and characterization procedure in more detail, and presents several techniques by which computational efficiency is improved. The resulting methodology is fast and relatively accurate in comparison with other tools, thus expediting the design exploration phase of project development and enabling broader optimization studies that might include typically ignored variables such as heliostat dimensions, tower position within land boundaries, and heliostat spacing parameters. Figure 1.5 shows an example heliostat field layout, receiver flux intensity
map, and aimpoint plot generated using SolarPILOT with ideally focused heliostats (Figures 1.5(a), 1.5(c), 1.5(e)) and with flat heliostats (Figures 1.5(b), 1.5(d), 1.5(f)), illustrating the breadth and non-trivial nature of solar field design and characterization. Chapter 2 explores these issues in more detail.

1.3 Dispatch Optimization

Thermal energy storage is an essential feature of CSP because it enables operational flexibility, and dispatch optimization is the process of identifying a solar field and power cycle operation schedule that maximizes the value of generated electricity. Energy dispatch can be targeted for high-value time periods, and it can be used to reduce both financial and performance O&M costs. For example, an optimized dispatch schedule may retain a small but sufficient quantity of energy at the end of one operational day in order to more efficiently start the next day, or it may choose to generate power at a reduced rate to conserve stored energy and avoid shutdown altogether. Optimized dispatch may also anticipate resource or pricing variability to maximize revenue, and the resulting modified operational scheme necessarily impacts the initial optimal design and long-term maintenance requirements for the plant. The best plant design and maintenance scheme can only be identified when a representative operational scheme is in place, and optimized operational schemes can differ substantially from unoptimized ones.

Identifying an optimal dispatch schedule for CSP is a non-trivial exercise for the following reasons:

(i) power production may vary with time, and a particular time horizon of interest (e.g., one year) is discretized with a large number of time steps, each representing an independent variable for power production;

(ii) electricity generation from the power cycle requires consumption of thermal energy that is produced by the solar field, and these processes are largely independent because of the TES system; thus, independent schedules are needed for both subsystems that
Figure 1.5: Layout and flux results for identically defined systems in which heliostats are focused (a,c,e) and flat (b,d,f). Flux intensity is shown on the receiver surface, and the aimpoint plot shows position of the point on the receiver, relative number of heliostats (dot size), and average distance of heliostats (dot color) for each aim point.
account for the charge state of TES;

(iii) CSP is subject to operational modes, and transition from one mode to another requires that certain conditions or procedures be satisfied – for example, the power cycle cannot produce output until the start-up process has completed;

(iv) simulation accuracy is of high importance, and generation modeled by a mixed integer linear problem (MIP) lacks sufficient fidelity when taken in isolation of detailed engineering model results; and

(v) revenue-maximizing schemes may encourage frequent power cycle starts and stops, and a mechanism for valuing production continuity is necessary, both from the standpoint of plant operability and long-term equipment wear and tear.

This research develops methods and ultimately delivers a tool for realistic optimization of stored energy dispatch, ensuring model validity by directly integrating the dispatch optimization program within the SAM software as a “control signal provider.” In this way, SAM predicts system performance using detailed engineering models, but establishes a target generation profile using a simplified – but tractable – MIP formulation. This capability provides an improved understanding of best-practice operations for CSP with TES and suggests changes in design and maintenance policy that improves the overall value of CSP technology.

1.4 Modeling Tools and Resources

Exploring the tradeoff between technology cost and performance is possible with robust technology simulation software in which the detail of each subsystem is captured within the context of the entire power plant. NREL develops software tools for characterizing subsystem cost and performance (e.g., Solar Power tower Integrated Layout and Optimization Tool (SolarPILOT™)) and for predicting the productivity of the integrated power plant over the course of a year using measured weather data (e.g., System Advisor Model (SAM) [6]).
These essential tools provide a framework for accurately and quickly quantifying the impact of design and operational decisions.

SolarPILOT and SAM span the range of analysis from initial design to simulation and financial evaluation. SolarPILOT is a unique tool for layout, optimization, and optical characterization of the heliostat field. The software is capable of evaluating the tradeoff between heliostat cost and optical performance, the impact of mirror soiling and washing schedules both globally and in local regions within the heliostat field, and of selecting solar field design variables that minimize the expected cost of energy. SolarPILOT is available as a stand-alone software package and is utilized via an application programming interface as the optical simulation engine in SAM – NREL’s renewable technology assessment simulation tool. The SAM software combines performance, cost, and financial models for a variety of renewable energy technologies, and is used to predict total plant and subsystem productivity, detailed component behavior, and financial metrics including cost of energy, power purchase agreement price, and internal rate of return.

SAM’s CSP technology performance models are derived from a combination of engineering physical principles and (semi-)empirical correlations. The SAM Molten Salt Power Tower (SAM-MSPT) model [11] uses a streamlined version of the SolarPILOT optical simulation engine and detailed thermal models of the receiver, thermal storage, and power cycle subsystems. SAM has received continuous funding from the DOE since 2006, and currently SAM-MSPT supports a generalized and stable plant control algorithm and implements a short-time-horizon (deterministic) TES dispatch optimization model.

The outcome of a SAM-MSPT simulation provides a single metric of interest – typically, levelized cost of energy (LCOE) – though many different flavors of this metric exist. The process for obtaining such a metric involves a series of carefully orchestrated procedures. The first step is to define the input parameters, including system sizing, optical and thermodynamic performance characteristics, component geometries, and costs. Next, the SAM-MSPT model evaluates the system to determine an improved design relative to that of
the baseline system, manipulating receiver height and diameter, tower height, and heliostat field layout positions. This step utilizes the SolarPILOT simulation engine to balance the optical performance of the heliostat field against costs using a simplified capital cost and annual productivity estimate.

In the third step, SAM-MSPT invokes the SolarPILOT engine to characterize the optical efficiency and concentrated solar flux intensity on the receiver surface (which is a primary factor in thermal performance and receiver lifetime) at a selected set of sun positions throughout the year. The resulting data sets form surrogate interpolation models that can be quickly evaluated at each time step in a subsequent annual simulation, greatly improving simulation speed and adding little error to energy cost estimates. Next, SAM-MSPT evaluates the system over each hour of a “typical meteorological year” using aggregated weather data from the selected location. This model is perhaps the most complex of any in the set, as behavior in each subsystem is closely tied to the control algorithm, behavior in connected subsystems, and the energy state of the system in the previous time step. For example, the thermal efficiency of the power cycle depends on the temperature of the hot HTF entering the heat exchanger, and this temperature can vary with the source of the fluid (receiver or TES system, or a mixture thereof), or thermal losses in TES or other connection piping. In turn, the thermal efficiency of the receiver depends on how efficiently heat is utilized in the power cycle. Many implicit interconnections play an important role in determining the overall performance of the plant. Once the annual hourly simulation is complete, SAM-MSPT then calculates revenue, discounted lifetime costs, and financial metrics of interest.

This thesis is concerned with development of techniques that improve the computational efficiency and accuracy of solar field design and characterization processes (implemented in SolarPILOT), and the formulation, implementation, and application of dispatch optimization techniques within SAM-MSPT. These advances build upon the existing tools, but are distinct from the prosaic activities of engineering software development, relying more heavily on theoretical and academic principles. Nonetheless, the formulations – however arcane – are
readily applied because of the platform in which they are deployed.

1.5 Literature Review

This project spans several areas of research, including energy dispatch optimization, power plant operation, engineering process simulation with thermodynamic and optics contributions, and engineering design optimization. Contributions made in each field by other researchers therefore enable this project and are reviewed in this section.

Performance simulation of a CSP plant is nontrivial, as CSP is an amalgam of interacting subsystems whose individual behaviors are complex and depend on the energetic state of each subsystem, the current weather conditions, the desired plant production schedule, limited component operating regimes, and the original design of the plant. Power plants with TES can dispatch stored energy according to any number of schemes. Typically, a set of rules (heuristic) is defined whereby a control algorithm is able to compute whether and at what power level a plant should generate electricity. The rules govern whether storage should be charged, discharged, or idled, whether an auxiliary fossil backup system (if present) should be used to generate supplemental thermal energy, and whether the solar field should be deployed to collect energy. Heuristic dispatch models can include a variety of rules but necessarily increase in complexity and programming effort as the number or rules increases.

Implementations of heuristic dispatch models are readily available and include SAM [2], which controls TES dispatch for each time step (typically, hourly) based on the charge state of the TES system, the presence or absence of solar irradiation, the target power cycle electricity generation level, and several other rules [12]. Herrmann et al. (2004) [13] describe a heuristic approach for parabolic trough plant control that is similar to the method previously implemented in SAM. The heuristic allows storage charging when energy generated by the solar field exceeds the thermal power requested by the power cycle – thus prioritizing power generation over storage charging. If energy is available in TES and the power produced by the solar field falls below the desired thermal input to the power cycle, TES is discharged until it is empty. The heuristic emphasizes turbine production at full load but allows shifting
of the generation schedule to high-value time periods by reducing production in low-value periods.

The long-used Solergy [14] simulation software offers a similarly simplistic heuristic model, but also explores a separate and sophisticated heuristic dispatch approach that incorporates energy production forecasting and time-dependent pricing. The latter algorithm attempts to maximize revenue while minimizing discarded thermal energy due to underproduction from the turbine and minimizing the number of turbine starts. The strategy – dubbed MAXOUT – implements a complex set of rules that uses stored energy for various purposes, including (i) day-to-day carryover of thermal energy for morning start-up, (ii) scheduled dispatch that avoids storage overcharging, (iii) part-load operation of the turbine to conserve energy for high-value time periods, and other desirable plant operation features. While the apparent flexibility of this heuristic is comparable to models based on MIP formulations, the functionality was originally developed and described for only a single pricing schedule. It is unclear whether the model was expanded for applications beyond the original study.

Guédez et al. (2015) [15] more recently suggest another example of heuristic dispatch. Their method emphasizes dispatch during peaking hours and includes decision procedures for identifying peak production hours. Figure 1.6 shows their method for determining peak hours. In the figure, they use the notation \( j \) to represent the time step, \( Q_{SF,j} \) is the thermal power produced by the solar field in time step \( j \), \( Q_{SM=1} \) is the thermal power required by the power block, \( TES\%_{,j} \) is the charge state of TES in step \( j \), \( \dot{m}_{out} \) is the mass flow rate dispatched from TES, \( \dot{m}_{nom} \) is the nominal mass flow rate from TES, and \( \delta_1 \) and \( \delta_2 \) are user-specified threshold parameters. This process diagram shows how heuristic methods are often forced to simplify dispatch in order to make the problem tractable. In this case, the TES discharge rate is specified as either the design-point (nominal) value \( \dot{m}_{nom} \) or zero, but the optimal value may not be either option. However, Guédez et al. (2015) show that heuristics can be effective in improving the dispatch of particular configurations.
Formal dispatch optimization models have also been explored by several groups [1, 7, 16–21]. These models develop linear or mixed-integer linear programs to approximate electricity generation behavior and typically share several common attributes, including:

- “rolling time horizon” optimization, in which the dispatch profile is revisited on a daily basis, but the optimization time horizon extends beyond a single day, allowing for day-to-day carryover of thermal energy
- treatment of decision variables using energy balance terms
- separation of the engineering simulation model from the optimization model and solver in which parameter information passes unidirectionally from the engineering model to the dispatch optimization model with no feedback
- inclusion of power cycle start-up effects and – in some cases – receiver start-up effects

Wittmann et al. (2008) [18] define an optimization model that is integrated into the transient simulation but focuses on prioritizing high-value time periods and neglects start-up behavior. Recent work introduces stochastic boundary conditions as part of the set of considerations, but does not present a formulation or results from the stochastic model [19].
Cirocco et al. (2015) [20] develop a simplified model with fully linear terms, thus neglecting start-up and sequencing effects. Lizarraga-Garcia et al. (2013) [22] develop a nonlinear model that facilitates simultaneous optimization of design and operation of a novel CSP technology concept over short-term time horizons of a day and a week. One purpose of this study is to investigate the efficacy of electric resistance heaters as part of the larger CSP design, and, hence, the conclusions emphasize relevant results for this goal. However, the study shows the viability of applying nonlinear solution techniques to a design and operations optimization problem. Vasallo and Bravo (2016) [21] define and present a modeling approach for dealing with weather and pricing forecast uncertainty. Their model consists of a mixed integer quadratic problem (MIQP) for dispatch schedule optimization and a module that tracks the schedule that has been committed to as the dispatch horizon progresses through time. The forecast model is updated on an hourly basis, and each forecast update entails a recalculation of the optimal dispatch schedule subject to additional requirements that arise from the original solution for the daily time window. This model assumes that unit commitment is established on a daily basis according to a bidding process and cannot be revised during the day.

A number of non-CSP dispatch optimization models have been developed (e.g., [23–26]). García-González et al. (2008) [26] describe a stochastic optimization method for pairing variable energy production from wind turbines and dispatchable generation from a pumped-hydro source. Although the technologies differ substantially from CSP, the underlying coupling of variable energy production, supplemented by dispatchable generation from storage, is analogous. Methodologies explored in this area are applicable for this work.

1.5.1 Summary of Content

The thesis is organized into five chapters: the first and current has provided background and motivating material, the fifth and final chapter provides summary and conclusion material and outlines future work that may be derived from this research, and the intervening chapters report advances regarding solar field design and characterization, dispatch opti-
mization, and applied results, and are further previewed as follows. The second chapter describes a tool for design, optimization, and characterization of the power tower systems whose operations are modeled in more detail in Chapters 3 and 4. This effort is prerequisite to formulating accurate dispatch models, as the solar field production profile is derived directly from this model. The third chapter introduces a rigorous mathematical formulation whereby operational processes in a molten salt plant are described and optimized, and presents a case study exploring the benefits of dispatch optimization over traditional heuristic-based approaches. The novelty in our work lies in the fidelity of the MIP formulation to the molten salt power tower technology, and in the successful integration of our dispatch optimization model into the detailed techno-economic analysis SAM-MSPT tool. The fourth chapter describes an application of the techniques presented in Chapters 2 and 3 with focus on dispatch optimization outcomes for a project under development by an industry-leading technology provider.

The reader may note that portions of material within this document appear more than once, especially concerning Chapters 3 and 4. This approach is intentional, and reflects the conventions dictating inclusion of journal papers in a thesis format. Each of Chapters 2-4 comprise a journal paper submission, and consequently, each is presented in its entirety. With regard to the MIP formulation – which appears in Chapters 3 and 4 separately, the journal Interfaces encourages inclusion of the model formulation as an appendix along with the applied results. Hence, we first present and discuss the model in Chapter 3, then restate the model in Chapter 4 as an appendix. We ask that the reader bear this in mind when examining this document.
2.1 Abstract

A new Solar Power tower Integrated Layout and Optimization Tool (SolarPILOT) is developed and demonstrated. The tool uses the analytical flux image Hermite series approximation originally implemented in the DELSOL3 software developed by Sandia National Laboratory in the early 1980’s. By applying the analytical model to individual heliostat images rather than large groups or zones of heliostats, SolarPILOT can characterize a wide variety of heliostat field layouts. The individual heliostat modeling approach increases computational expense in comparison with DELSOL3, so SolarPILOT implements a number of improvements to the analytical approximation method to improve model accuracy and computational efficiency. Several of these methods are discussed in this paper, including dynamic heliostat grouping to reduce the expense of intercept factor evaluation, approximation of annual productivity with a subset of time steps throughout the year, polygon clipping to accurately calculate inter-heliostat shadowing and blocking, receiver and tower geometry optimization, and trigonometric image transformation to ensure analytical equation accuracy for small heliostats. SolarPILOT also integrates the SolTrace Monte-Carlo ray tracing engine, providing improved receiver optical modeling capability, a user-friendly front end for geometry definition, and side-by-side validation of the analytical algorithms.
2.2 Introduction

Power tower systems (also known as “central receiver systems”) are optically complex, using thousands of individually-tracking heliostats to reflect sunlight onto a stationary receiver throughout the day and the year. The angular acceptance window for the reflected image from a heliostat is typically very small, requiring tracking precision with an error distribution standard deviation on the order of 1 mrad or less. In addition, receiver operation typically requires that the incident flux density be maintained below a maximum value, and heliostat images must be strategically placed on the receiver to achieve a workable distribution [27–29] that extends the receiver material lifetime and minimizes optical interception losses. The redirection of sunlight by the heliostat field is also subject to a series of losses that depend on the heliostat’s position relative to the receiver, the position and orientation of neighboring heliostats, the position and apparent shape of the solar disc, the particulate content in the atmosphere, the geometry of the heliostat, optical errors in the heliostat, and the heliostat field operation strategy. Many of these losses are dynamic and must be modeled over a range of conditions in order to adequately characterize the likely performance of a CSP plant [11]. Consequently, computer software has been used to generate solar field geometry and characterize its performance since the late 1970’s [30–33].

The history of available software programs extending from first-generation tools through current solutions is well-documented [4, 34]. A number of programs have been developed to support the various stages of analysis that are necessary to characterize system performance. Tools such as the University of Houston Codes (UHC - also known as the RCELL suite) [33], DELSOL3 [35], TieSOL [36], and HFLCAL [37] can generate solar field geometry programmatically. Other programs such as MIRVAL [31], HELIOS [38], STRAL [39], Tonatiuh [40], and SolTrace [41] are capable of detailed field characterization but are not designed to quickly generate and optimize solar field geometry. (DLR has developed an extension for MIRVAL that facilitates automated field layout [34].) Finally, given a particular geometry, several codes are capable of characterizing the annual performance of tower systems, includ-
ing Solergy [14], SAM [42], and the TRNSYS STEC library [43]. Because these various tools emphasize different aspects of power tower solar field design or characterization, each must be used deliberately within the scope of the problem that it addresses.

2.2.1 Modeling approaches

The aforementioned tools characterize optical performance using one of two general approaches: analytical (or semi-analytical) approximation or Monte-Carlo ray-tracing (MCRT). The basis for analytical methods lies in modeling a reflected image with a closed-form density function. The reflected image density function describes the intensity of light (flux) as a function of position on a projection plane. Under the theoretical conditions that incident flux on the reflector is perfectly collimated, that the reflector geometry is perfectly parabolic, and the projection plane contains the focal point of the reflector, the reflected image is infinitely small and of infinite intensity. In practice, however, various sources of reflection error cause the image to assume the form of a distribution. Most simply, an image can be approximated using a Gauss-normal distribution with standard error deviation defined in one or two dimensions.

Multiple physical effects can introduce reflected image error. For example, light from the sun is not perfectly collimated but instead is described by a probabilistic distribution of incident angles. Reflector surface defects, tracking error, and imperfect or non-ideal focusing of the reflector can also affect the reflected image. As these sources of error increase, the reflected image size also tends to increase. One approach for modeling multiple error factors is to simply convolve the various error sources as independent normal distributions into a single normal distribution described by a standard deviation in each dimension. This approach limits the shapes of the reflected images that can be modeled, but may be appropriate for heliostats with certain optical properties. A more nuanced approach utilizes the truncated Hermite polynomial series to describe the image shape in two dimensions [30, 32], originally developed by the University of Houston. This method accommodates non-normal sun shape distributions and can accurately represent flux patterns for flat, focused, or canted heliostats.
at a variety of tracking angles. This method is the basis for DELSOL3 and the University of Houston Codes (UHC), which are related to RCELL. The primary advantages of this approach are its computational efficiency in comparison with ray-tracing methods, flexibility in describing complex flux shapes with continuous functions using relatively few expansion coefficients, and its corresponding ability to accurately determine intercepted power on the receiver using integration by quadrature.

One limitation of the Hermite method is that directional information is not preserved in the analytical approach. This makes analysis of multiple reflections or beam-spread within a cavity receiver non-trivial [44, 45]. Furthermore, unlike MCRT, shadowing and blocking must be handled independently of flux image calculations, and accounting for partial shadowing or blocking exclusions in the final image shape is not straightforward.

The MCRT approach is widely used in optical analysis as it offers easy implementation, flexibility in the geometry that can be modeled, preservation of directional information through multiple reflections, and a clear physical analog. Codes such as SolTrace, MIRVAL, and Tonatiuh offer solutions for power tower modeling that can account for the various error sources and shapes, and can characterize non-ideal reflector surfaces as obtained by high-resolution surface slope measurements (e.g., VSHOT [46]). The primary disadvantage of MCRT approaches is their relatively long run times. This is especially true for power tower heliostat fields where ray intersections are possible over a large number of geometrical entities and many rays are required to obtain convergence. However, Izygon (2011) and others have developed a program that utilizes graphical processing units (GPUs) to provide enhanced parallelization that greatly reduces run time [36] but requires specific graphics processing hardware.

With these considerations in mind, the Hermite analytical approach has traditionally been used in optimization tools where many simulations are required to determine an optimal system configuration. For example, the DELSOL3 code was implemented in System Advisor Model [47] and was capable of first generating an approximately optimal solar field layout,
tower height, and receiver size, then characterizing the solar field efficiency and receiver flux profile over a range of solar positions in fewer than ten seconds using a standard laptop computer. In comparison, a single run in SolTrace for a power tower system with 5,000 heliostats and a peak flux uncertainty of 1.1% (1 × 10^6 rays) requires of less than two hours on a standard laptop computer with Intel Core i5 running 4 parallel threads. By integrating the analytical and MCRT engines, SolarPILOT provides rapid layout capabilities with more flexible MCRT characterization options.

2.3 Tool description

SolarPILOT provides layout, characterization, parametric simulation, plotting, and optimization capabilities via a graphical user interface (Figure 2.1). Limited functionality is also currently available through a C++ application programming interface (API). SolarPILOT has been integrated into SAM via the API, and now serves as the power tower characterization engine. An important aspect of SolarPILOT is the integration of both analytical and raytrace methods in the software. The following sections describe the methodologies in more detail.

Figure 2.1: SolarPILOT graphical interface showing a selected region of the heliostat field after an afternoon simulation with shadowing efficiency data overlay.
2.3.1 Analytical methods

SolarPILOT extends the Hermite method implemented in DELSOL3 by applying the optical model to individual heliostats to simulate whole-field performance. Although DELSOL3 is capable of simulating fields with several thousand individual heliostats, optimization is done using a coarse cylindrical-coordinate grid. SolarPILOT’s higher-resolution approach differs from DELSOL3 in its treatment of individual heliostats in all phases of calculation and optimization. The implementation of the Hermite model for individual heliostat images requires several enhancements to maintain computational speed and accuracy. Specifically, this tool implements a novel method for dynamic heliostat grouping to reduce the expense of intercept factor evaluation, methods for approximating annual productivity with a subset of time steps throughout the year, a polygon clipping method to accurately calculate inter-heliostat shadowing and blocking, methods for receiver and tower geometry optimization, and a trigonometric image transform algorithm that maintains intercept factor accuracy for small heliostat images. Each of these improvements enables SolarPILOT to perform accurate and efficient computation.

2.3.1.1 Review of the DELSOL3 Analytical Method

DELSOL3 approximates each zone as a single representative heliostat in a radial-stagger arrangement, and performance is evaluated at the center point of the zone. Shadowing and blocking are also calculated at this point, assuming a regular distribution of surrounding heliostats also in the radial-stagger arrangement. The code adjusts for “slip planes” (discontinuities in the solar field layout) by reducing the shadowing and blocking loss proportionally to the number of heliostats removed at the slip plane boundary [35]. These assumptions work well for regular, symmetric heliostat fields with a large number of heliostats in a radial-stagger layout. However, current field layout techniques often differ from this historical approach, and alternative solutions offer improved efficiency, reduced land area, exclusions for culturally sensitive areas or topographic features, and accommodation
for uneven land as exemplified by [48–50].

The computational speed advantage for the Hermite series approximation lies in its application of characterization coefficients that do not all require recalculation for each heliostat or simulation. The analytical form of the flux intensity profile as it appears on the receiver plane is shown in Eq. 2.2, taken from [30].

\[
F(x, y) = \frac{1}{2\alpha_x\alpha_y} \exp \left[ -\frac{1}{2} \left( \frac{x}{\alpha_x} \right)^2 - \frac{1}{2} \left( \frac{y}{\alpha_y} \right)^2 \right] 
+ \left\{ \sum_{i=0}^{l} \sum_{j=0}^{J-i} A_{i,j} H_i \left( \frac{x}{\alpha_x} \right) H_j \left( \frac{y}{\alpha_y} \right) \frac{1}{i!j!} \right\}
\]

(2.1)

The equation assumes that the flux intensity can be modeled primarily as two-dimensional normal distribution, but the intensity at any position \((x, y)\) is modified by evaluating a series expansion with Hermite polynomial terms \(H_i(x), H_j(y)\), and \(A_{i,j}\). The components of the coefficients are evaluated for a given sun shape, mirror geometry, optical error contributions, and relative position to the tower. These individual terms are evaluated only when they change during the simulation, so a flux profile can be quickly developed for heliostats of identical geometry once the initial coefficient analysis is complete. The distribution is normalized by two coefficients – \(\alpha_x\) and \(\alpha_y\), which represent the standard deviation of the image distribution in the \(x\) and \(y\) directions relative to the image plane. Coefficients for mirror geometry, sun shape, and optical error need only be evaluated once because they are independent of sun position and heliostat orientation. The final flux intensity model depends on sun position and heliostat orientation, and these effects are accounted for by combining the constant distribution coefficients with position-dependent coefficients. Sun shape is modeled as a time-independent intensity distribution, though in reality sun shape can vary with local atmospheric composition and sun position. However, heliostat optical errors typically dominate the error distribution, and sun shape is a relatively minor contribution to the overall concentration error.
DELSOL3 evaluates the fraction of the heliostat image that is intercepted by the receiver (intercept or spillage efficiency) using a numerical integration method known as Gauss-Hermite quadrature [30]. Each heliostat image is modeled using a 2D Gauss-Hermite polynomial for which no analytical integral exists, but the integral can be approximated by evaluating the flux density expression at various points in the distribution. By carefully choosing the location of these points to coincide with abscissa in the polynomial expression, relatively few points are required to calculate the integral. DELSOL3 uses this algorithm along with a weighting function for each point (that has also been derived analytically) to determine the intercept factor for each image with only 16 points. The integral bounds coincide with the extents of the receiver, and the evaluation points lie in between these extents.

2.3.1.2 Shadowing and Blocking

SolarPILOT calculates shadowing and blocking using a vector projection and clipping method. Neighboring heliostats are tested for potential interference by projecting vectors from the heliostat corners along the direction of either the tower (blocking) or sun position (shadowing). If a projected vector intercepts an adjacent heliostat, blocking or shadowing are enforced according to the position of the interception. This method assumes that neighboring heliostats lie in parallel planes – a good assumption for all but very small solar fields where tracking angles differ significantly between neighboring heliostats. This assumption results in the simplification that shadowed or blocked regions are rectangular, which simplifies the computation without affecting accuracy. Overlap of shadowing and blocking is neglected, so the blocking-shadowing efficiency is conservative.

The shadowing and blocking algorithm is as follows:

i. Each heliostat $J$ is assigned a list of neighbors (see §2.3.1.3) that may block or shadow ("interfere" with) the heliostat. An interfering heliostat is subsequently denoted $K$. 

26
ii. A vector aiming at subject of interference (the receiver for blocking or the sun position for shadowing) is calculated for the interfering heliostat $\hat{i}_K$.

iii. Heliostats are tested for the possibility of interference:

   a. The first test requires that the interfering heliostat $K$ is within view of the interfered heliostat $J$. The dot product is calculated between the heliostat normal vector and the interfering heliostat subject vector.

   \[ v = \hat{n}_J \cdot \hat{i}_K \]  

   If the dot product is non-positive, $K$ cannot interfere with $J$ and the loss is zero.

   b. The maximum interference length is calculated for heliostat $J$ based on the position in space of each heliostat $P_J$ and $P_K$, the heliostat structure height $h_J$, the interfering heliostat tracking vector $\hat{t}_K$, and the zenith angle of the heliostat tracking vector $\phi_{t,K}$.

   \[ L_{int} = \frac{P_{K,z} - P_{J,z} + h_J \sin \phi_{iK}}{\sqrt{t_{K,i}^2 + t_{K,j}^2}} + h_J \hat{t}_{K,k} \]  

   If the distance separating the two heliostats in question is greater than $L_{int}$, the heliostats cannot interfere and the loss is zero. $L_{int}$ is limited to $100 \times h_J$ during very low sun elevation angles to reduce the number of potentially interfering heliostats and the associated computational requirement.

iv. The interference vector $\hat{i}_K$ is projected from the two top corners of $K$ onto a plane containing $J$. The plane intersection points are tested for containment within $J$.

v. The interfered region area is calculated based on the intersection position of $\hat{i}_K$ within $J$. The total interference efficiency is equal to the complement of the interference area divided by the total heliostat area.
2.3.1.3 Dynamic Heliostat Grouping

Power tower solar fields contain thousands or tens-of-thousands of individual heliostats. Often, performance of neighboring heliostats is very similar, and one heliostat can be used to represent the performance of a small group of neighboring heliostats. The most accurate optical performance calculations consider each heliostat individually (SolarPILOT default behavior), and the least accurate consider all heliostats in a group to have identical performance, including shadowing, blocking, intercept factor, atmospheric attenuation, and cosine losses (DELSOL3 behavior). Accuracy improves as the zone size approaches the domain of a single heliostat.

Accuracy can also improve by considering heliostat loss mechanisms separately and only approximating those losses that are computationally expensive to calculate. For example, cosine loss is one of the most significant losses but its computational expense is trivial, so each heliostat can be considered individually. Optical intercept factor (the amount of light captured by the receiver from any heliostat image) is equally significant but is comparatively much more expensive to calculate. Therefore, we have adopted a mixed approach of calculating simple losses such as cosine and attenuation individually and the expensive intercept factor loss using a zonal approximation.

These so-called optical zones include groups of neighboring similarly performing heliostats. The challenge with the zonal approach is that the intercept factor can depend strongly on position, and change in intercept factor is nonlinear as a function of radial and circumferential position. Consider Figure 2.2 showing intercept factor as a function of radial position for a particular heliostat and receiver configuration. The intercept factor stays constant until the image begins to spill off the receiver near 250m radius. The intercept factor then drops precipitously but eventually stabilizes as distance from the tower increases. This case is provided as a qualitative example, though the exact intercept as a function of position depends on heliostat size, heliostat position, optical parameters, receiver geometry, and sun position.
Both radial and circumferential position can impact intercept factor, especially for receivers with a planar aperture (flat plate or cavity receivers). The derivative of intercept factor with respect to either radius $r$ or azimuthal heliostat position $\beta$ can be determined for planar and cylindrical receivers. The higher the value of these derivatives, the more quickly the intercept factor changes with position, and the smaller the group of heliostats that can be represented by a single calculation.

SolarPILOT subdivides the heliostats accordingly, creating a mesh in circumferential coordinates which has varying density in both azimuthal and radial dimensions. The mesh generation is handled recursively such that a particular region is subdivided if the change in intercept factor across the zone is greater than the allowable limit, and the resulting grid cells are subsequently and likewise analyzed. Figure 2.3 shows an example of an optical mesh for a north-based field. The highest gradient in intercept factor is concentrated near regions of high flux incidence angle.

**Mapping heliostats to optical zones**

The approach discussed above generates an efficient and physically meaningful optical mesh based on local intercept factor derivatives. This mesh is nonregular, and each element may have different radial and azimuthal extents. Therefore, no simple transformation exists
between heliostat position in Cartesian coordinates and zone location. The zone to which a heliostat should belong is computationally nontrivial to determine. In the worst case, the number of assignment computations would be equal to the product of the number of zones and the number of heliostats.

To circumvent this problem, we have devised a binary element tree that guarantees that a small number of computations $n_{c_{\text{max}}}$ are required to locate a heliostat within some tolerance $\delta$. The computational expense for the binary element tree is logarithmic, with the worst case being:

$$n_{c_{\text{max}}} \leq 2 \left[ \log(2)^{-1} \max \left\{ \log \left( \frac{\Delta r}{\delta r} \right), \log \left( \frac{\Delta \beta}{\delta \beta} \right) \right\} \right]$$

In order to demonstrate the computational efficiency of this method, the following example is provided. A typical field will have a radial extent of $\Delta r = r_{\text{max}} - r_{\text{min}} = (8 - 1)h_{\text{tower}} = 7 \cdot h_{\text{tower}}$ where $r_{\text{max}}$ and $r_{\text{min}}$ equal the minimum and maximum heliostat extents radially normalized by the tower height $h_{\text{tower}}$. A heliostat’s radial position can be uniquely described with coordinate tolerance of $\delta r = 0.01 \cdot h_{\text{tower}}$ since this corresponds to a distance less than...
the minimum heliostat spacing for a typical field. In the azimuthal direction, the heliostat separation at $r_{\text{max}}$ is $\Delta \beta = 2\pi h_{\text{tower}} \cdot r_{\text{max}}$, and we use $\delta r = \delta \beta$. The number of computations required to locate a point in the field for this example is no more than $n_{\text{cmax}} = 20$. The total number to locate each of the $N_h$ heliostats is then proportional to $N_h \cdot 20$, which is a vast improvement over $N_h^2$ for the worst case.

The binary element tree works by dividing the coordinate space into halves radially and azimuthally. Each half is then divided again and again until the size of the zone is sufficiently small. Divisions are done alternatingly between radial and azimuthal directions. The decision to select the inner or outer (and clockwise or counter-clockwise) half is determined with an integer value. Inner and counter-clockwise values are denoted with '0' and outer and clockwise values with '1' – hence the binary structure.

The required resolution (size) of the zone determines the number of characters in the identifying key. Larger zones require fewer characters to uniquely identify them, while smaller zones require more. This procedure lends itself to mesh structures with variable element size, which is an important feature for SolarPILOT implementation. Each heliostat is assigned a binary coordinate tag that uniquely identifies its location using the same binary procedure. Any heliostat that falls within a particular zone will begin with the same binary character string as the zone itself, enabling quick association of heliostat-to-zone. The binary mesh tree is recursive such that each element independently can decide whether to split or remain intact. The algorithm also allows unidirectional splitting if the required tolerance has been met in only one direction. That is, if the mesh reaches sufficient resolution regarding derivatives in the radial direction, additional splits are permitted in the azimuthal direction only while the radial extent remains unchanged. Once the mesh has been defined in the first element after a split, the algorithm calls again to define the mesh in the remaining half. The resulting data structure resembles a tree, with the largest elements branching into many sub-elements which can branch further. A similar but distinct $k$-$t$ binary tree method is described in [51]. Only “terminal” elements that is, elements that contain no sub-elements
- are permitted to accept heliostats into their group. This ensures the uniqueness of each element.

The impact of dynamic grouping on the heliostat field layout and expected solar field annual energy production is quantified in Figure 2.4. The number of heliostat field dislocations (positional differences in the layout) and the annual energy error as simulated in SAM are shown for various zone tolerance values. As the tolerance increases, so does the zone size and the error in the intercept factor approximation, leading to selection of sub-optimal heliostats for the final layout. The cases shown are relative to the reference case defined in Table 2.1 below with dynamic grouping disabled. Note that dynamic grouping with a tolerance value of 0.01 reduces computational time by approximately 50%.

Figure 2.4: The impact of dynamic grouping on field layout and annual energy production.
2.3.1.4 Efficient Annual Performance Prediction

SolarPILOT selects the heliostat positions to include in the final layout by estimating the annual performance of each heliostat in the field, then ranking their performance and selecting the most productive heliostats first. Although heliostat field systems are optically complex, their performance over time is reasonably tracked as a linear summation. That is, for approximately similar sun positions (and thus optical efficiencies), the power delivered by the field is the summation of the set of solar resource values times the field area times the average optical efficiency. Because it is computationally expensive to evaluate field optical performance, it is often impractical to determine annual field performance by simulating all daytime hours in the year. Instead, a subset of hours can be simulated and the annual approximation projected from that sample. SolarPILOT includes several methods and tuning parameters to configure the annual performance estimate simulation set. These are:

*Single simulation point*

The field performance is evaluated at a single sun position and solar resource. Each heliostat’s performance is characterized by a single production value.

*Annual simulation*

Every daytime hour of the year is simulated, and each heliostat’s performance is characterized by the accumulation of all hours in the year. This option – while thorough – is computationally expensive and most often unnecessary.

*Limited annual simulation*

A subset of days and hours of those days are chosen at regularly spaced intervals throughout the year for simulation. At each hour, corresponding weather data is used to determine heliostat field productivity. Each heliostat is characterized by the set of productivity values generated in the simulation. A sufficiently large number of days must be used to achieve convergence, and the number depends on the seasonal and daily weather variability. Convergence is typically achieved with 12 simulation days at an hourly or bi-hourly resolution.
Representative profiles

This option mimics the Limited annual simulation, but generates averaged weather profiles for the selected days rather than using specific weather days from a weather file. This option demonstrates convergence with 4 simulation days and bi-hourly resolution and is observed to be the most effective option. Figure 2.5 shows the impact on layout “dislocations” – that is, the number of positional differences in a heliostat field layout – for the reference plant defined later in Table 2.1 as a function of the number of simulation days and the hourly frequency at which simulation occurs. Also shown is the impact of these parameters on annual energy production as simulated in SAM, which is trivially small in all cases. This demonstrates that for the purposes of techno-economic analysis, additional computational expenditure in the form of increasing the sampled hours and days is not beneficial.

Annual efficiency map

SolarPILOT can also generate a lookup table of optical efficiency as a function of solar position, then run an annual simulation drawing from the lookup table rather than generating performance data from the first-principles model.

In addition to climate effects, local markets can shape the temporal value of power production. A plant optimized for revenue would consider increasing power production during the most profitable hours of the year at the expense of overall electricity production. SolarPILOT allows specification of temporal revenue weighting factors that are considered during layout. Some utilities such as Southern California-Edison, San Diego Gas & Electric, and Pacific Gas & Electric provide payments to electricity producers based on time-of-day and day-of-the-year that reflect increased demand during certain time periods.

2.3.1.5 Field layout methodology

SolarPILOT is designed to generate heliostat field layouts with individual heliostat coordinates. Several layout options are possible, including permutations on the radial-stagger layout and a “corn field” layout. The code is easily extendible to generate alternative layout
Figure 2.5: The impact of the number of days and hourly simulation frequency used during field layout on layout dislocations (top) and annual energy error (bottom) as simulated in SAM. The cases shown are relative to a layout in using 50 days at two-hour frequency.

patterns, and heliostat coordinates can be imported and simulated by the user. The layout procedure is as follows:

i. Generate all possible heliostat positions within the land boundaries.

ii. Place heliostats at the positions according to the heliostat geometry template rules (if applicable).

iii. Simulate the performance of all heliostats at the field design simulation time step(s) specified by the user with weather data (if applicable).

iv. Sort heliostats by performance-to-cost ratio.
v. Simulate solar field performance at the design point solar position and direct normal irradiance. The single design point may be noon on the summer solstice, noon on the equinox (spring), noon on the winter solstice, solar zenith, or a user-specified sun position.

vi. Select the first $N$ heliostats that generate sufficient power to meet the design-point thermal power requirement.

Land boundaries can be specified point-wise as a set of polygons. Each polygon can represent an “inclusion” area or region of exclusion. Land bounds may also be specified as minimum and maximum radial limits that either scale with tower height or are fixed distances. Heliostat positions are generated within the entire land boundary considering all of the constraint types that are in use. Figure 2.6 shows a heliostat field built within a non-circular boundary.

2.3.1.6 Intercept Factor for Small Images

One challenge with adapting the Hermite approximation method to individual heliostats is the small size of the heliostat image relative to that of the receiver surface. Intercept factor is calculated for a Hermite expansion flux density model using Gaussian quadrature, which is a numerical technique that approximates the definite integral using a sum of function evaluations $f(x_i)$ with weights $w_i$ (e.g., Eq. (2.5)).

\[
\int_{-1}^{1} f(x) dx = \sum_{i=1}^{N} f(x_i)w_i \tag{2.5}
\]

As applied in DELSOL3, and subsequently SolarPILOT, the method uses a grid of $N = 16$ points to evaluate the density equation. A problem arises when the heliostat image is significantly smaller than the quadrature grid. Gaussian quadrature assumes that the function is well-approximated by a polynomial function in the region of evaluation, and thus gives poor results for images that are much smaller than the apparent receiver size (e.g., 1 $m^2$ heliostats on a 10 $\times$ 10m receiver). This problem can be corrected by scaling the quadrature grid.
Figure 2.6: Land-restricted layout with land boundaries overlaid in the top right corner. The available land area is defined by a single inclusion area and two exclusion regions.

...
This process is straightforward for cylindrical receivers. Each heliostat aimpoint lies at some vertical position along the center-axis of the receiver as it appears to that heliostat. In effect, the heliostat image—while vertically displaced from the receiver centerline—is always centered horizontally on the apparent rectangle of the receiver. The image is elongated in the vertical direction in proportion to the cosine of the angle between the receiver surface normal and the incident image vector (heliostats closer to the tower are distended more so than distant heliostats). Importantly, the heliostat images are not significantly skewed or rotated in the horizontal direction because the incident vectors from each heliostat have no azimuthal component, only vertical displacement. The consequence of these observations is that the quadrature grid can be scaled in a very simple manner:

\[
\begin{align*}
  w_{\text{quad}} &= \min[4\sigma_x, r_{\text{rec}}] \\
  h_{\text{quad}} &= h_{\text{rec}}
\end{align*}
\]

(2.6)  
(2.7)

The quadrature grid width is the minimum of four times the x-direction image size and the receiver radius \( r_{\text{rec}} \), while the quadrature height \( h_{\text{quad}} \) is always left as the receiver height \( h_{\text{rec}} \). This approach was implemented in the original DELSOL3 code and has proven to be adequate.

The cavity and flat-plate receiver case is somewhat more difficult. With the view angles between each heliostat and the receiver surface varying significantly over the extent of the heliostat field, the quadrature grid size cannot be scaled according to \( \sigma_x, \sigma_y \) alone. The issue is illustrated in Figure 2.7. The first case (left) shows a heliostat image projected onto the receiver plane. The quadrature limit of the image is drawn at \( 5\sigma_x, 5\sigma_y \), and dotted tangent lines indicate the revised integration width for the grid. The same image projected from different points in the field result in widely differing quadrature limits, as shown in the remaining cases (center, right). Furthermore, the difference between image and receiver coordinate systems is quite pronounced. These complications apparently prevented any practical quadrature scaling method from being implemented in DELSOL3, and the
resulting behavior could be severe, as illustrated in Figure 2.8. Figure 2.8(a) shows the resulting “optimal” layout positions for a large flat-plate receiver with small heliostats. The unexpected gap corresponds to images that are small enough and oriented in such a way as to be overlooked by the integration algorithm. The layout shown in Figure 2.8(b) uses the corrected scaling algorithm.

![Diagram showing heliostat image on the receiver plane in three position scenarios. Bounding-box image extents are shown for each case, indicating the dependence of “scaled receiver” size on the heliostat’s receiver view.]

The corrected scaling algorithm follows a simple procedure:

i. Given the position and orientation of the heliostat and receiver, the receiver corner points are translated into the coordinate system of the heliostat image plane. The “image plane” is a theoretical plane that is normal to the vector following the reflected heliostat image.

ii. The quadrature grid must be scaled while maintaining its original receiver coordinate system. The slope of the quadrature grid bounds is equal to the slope of the receiver bounds when projected onto the image plane. The slopes are calculated using the translated receiver corner point coordinates in step (i).
iii. The quadrature limit is determined by locating the intersection point between the ellipse of the projected image and a tangent line of slope equal to that calculated in step (ii). (See dotted lines in Figure 2.7.)

iv. The radius of the ellipse at the two tangent points give the quadrature width and height in the image plane coordinate system.

v. The final quadrature width and height are calculated by translating the width and height from step (iv) back into the receiver plane coordinate system.

The key calculation in this process is the expression relating the ellipse radius to the slope of a tangent line. In particular, we wish to express the radius of the ellipse as a function of tangent line slope. The equation of an ellipse with major and minor axis dimensions $\sigma_x$, $\sigma_y$ is shown in Eq. 2.8:

$$1 = \left( \frac{x}{\sigma_x} \right)^2 + \left( \frac{y}{\sigma_y} \right)^2$$

$$y = \sigma_y \sqrt{1 - \left( \frac{x}{\sigma_x} \right)^2}$$

(2.8)
The derivative $\frac{dy}{dx}$ is:

$$\left( \frac{dy}{dx} \right) = \frac{-\sigma_y x}{\sigma_x \sqrt{\sigma_x^2 - x^2}} \quad (2.9)$$

Equation 2.9 can be solved for $x$, and Eq.’s 2.8 and 2.9 can be substituted into the radius equation $r^2 = x^2 + y^2$ as shown in Eq. 2.10.

$$r^2 = \frac{\sigma_y^4 \left( \frac{dy}{dx} \right)^2}{\sigma_y^2 + \sigma_x^2 \left( \frac{dy}{dx} \right)^2} + \sigma_y^2 \left( 1 - \frac{1}{\sigma_x^2} \left( \frac{\sigma_y^4 \left( \frac{dy}{dx} \right)^2 - \sigma_y^2}{\sigma_y^2 + \sigma_x^2 \left( \frac{dy}{dx} \right)^2} \right) \right) \quad (2.10)$$

which simplifies to Eq. 2.11.

$$r^2 = \frac{\sigma_y^4 + \sigma_x^4 \left( \frac{dy}{dx} \right)^2}{\sigma_y^2 + \sigma_x^2 \left( \frac{dy}{dx} \right)^2} \quad (2.11)$$

This relationship provides a closed-form calculation of the required quadrature width given receiver corner coordinates projected onto the heliostat image plane.

### 2.3.2 SolTrace integration

SolTrace is a MCRT code designed for solar applications [41]. Incoming solar radiation can be characterized in any variety of shapes, and the code handles optical error distributions and multiple reflections. SolarPILOT has integrated SolTrace directly through an application programming interface (API) that calls to SolTrace’s core tracing functions. The primary strength of SolTrace is characterizing the performance of well-defined geometry, and typical use involves definition of geometry including tracking angles externally or in the built-in scripting language. As SolarPILOT is designed for power tower system layout, it serves as an interface for geometry definition, rapidly generating the required system geometry for SolTrace runs. The combination of analytical and MCRT tools means SolarPILOT can quickly calculate optimized heliostat aim points using analytical characteristics, then generate a detailed MCRT flux profile using SolTrace. This capability is especially useful for cavity-type receivers that analytical methods cannot adequately characterize because of complex view factors and multiple reflections.
While SolTrace offers several key advantages compared to analytical methods such as multiple-reflection characterization and the capability to analyze more complex geometries, it does not provide detailed optical loss information described by loss mechanism. The reported results from a SolTrace run consist of the number of intersected rays on all modeled surfaces. Information on what proportion of the optical loss is due to cosine, atmospheric attenuation, spillage, etc, is not directly calculated. Therefore, the best use of MCRT techniques is in conjunction with an analytical approach that provides insight into loss mechanisms.

2.4 Model Verification

SolarPILOT was developed as an extension to DELSOL3. Therefore, the performance of SolarPILOT is compared to DELSOL3 to verify the correct implementation of the new model. Because SolarPILOT includes several improvements over DELSOL3 in field layout techniques, characterization accuracy, and other features previously discussed, the comparison study matches thermal power delivered under reference conditions at the base of the tower (i.e., after reflective, convective and emissive, and piping losses) and inspects the various loss components modeled by each software package. The case study evaluates a cylindrical molten salt receiver with large multi-paneled heliostats. The field layout is radial-stagger, and all input parameters are matched as closely as possible to define analogous cases. Table 2.1 shows a summary of input parameters for each case. The primary difference between cases is the design weather model, as DELSOL3 uses a clear sky approach as exemplified by the Meinel formulation, while SolarPILOT is capable of using historical weather data. Use of the latter option complicates the analysis by relaxing the assumption of solar resource symmetry about solar noon, but adds flexibility by choosing those heliostats that maximize power production under the expected weather conditions. For example, a location that tends to be subject to afternoon cloudiness may orient the field to increase efficiency in the morning when sunlight is available. Ultimately, for the example provided, the differences in the layout between the two weather file models is only 17 heliostat positions, which translates into a trivially small impact on annual energy production, as discussed in Section 2.3.1.
Table 2.1: Parameters for the comparison case study and simulation results.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Units</th>
<th>DELSOL3</th>
<th>SolarPILOT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal power output</td>
<td>MWt</td>
<td>669.9</td>
<td></td>
</tr>
<tr>
<td>Reference DNI</td>
<td>W/m²</td>
<td>950</td>
<td></td>
</tr>
<tr>
<td>Heliostat area</td>
<td>m²</td>
<td>144.4</td>
<td></td>
</tr>
<tr>
<td>Heliostat total refl.</td>
<td>%</td>
<td>89.1</td>
<td></td>
</tr>
<tr>
<td>Tower height</td>
<td>m</td>
<td>203.3</td>
<td></td>
</tr>
<tr>
<td>Receiver height</td>
<td>m</td>
<td>20.41</td>
<td></td>
</tr>
<tr>
<td>Receiver diameter</td>
<td>m</td>
<td>17.67</td>
<td></td>
</tr>
<tr>
<td>Receiver absorptance</td>
<td>%</td>
<td>0.94</td>
<td></td>
</tr>
<tr>
<td>Azimuthal spacing factor</td>
<td>-</td>
<td>n/a</td>
<td>1.96</td>
</tr>
<tr>
<td>Slip plane reset limit</td>
<td>-</td>
<td>4/3</td>
<td>1.31</td>
</tr>
<tr>
<td>Design weather model</td>
<td>-</td>
<td>Meinel mod.</td>
<td>TMY3 data</td>
</tr>
<tr>
<td>Max. field radius</td>
<td>( \cdot h_{tower} )</td>
<td>7.5</td>
<td>9.0</td>
</tr>
<tr>
<td>Reference design time</td>
<td>-</td>
<td>Equinox, solar noon</td>
<td></td>
</tr>
<tr>
<td>Compared simulation time</td>
<td>-</td>
<td>Solstice, solar noon</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Result</th>
<th>Units</th>
<th>DELSOL3</th>
<th>SolarPILOT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of heliostats</td>
<td>-</td>
<td>8,947</td>
<td>8,945</td>
</tr>
<tr>
<td>Power incident on rec.</td>
<td>MWt</td>
<td>767.93</td>
<td>766.87</td>
</tr>
<tr>
<td>Power at receiver base</td>
<td>MWt</td>
<td>680.77</td>
<td>679.46</td>
</tr>
<tr>
<td>Cosine efficiency</td>
<td>%</td>
<td>80.3</td>
<td>80.6</td>
</tr>
<tr>
<td>Blocking efficiency</td>
<td>%</td>
<td>99.3</td>
<td>99.0</td>
</tr>
<tr>
<td>Shadowing efficiency</td>
<td>%</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>Atmospheric transmit.</td>
<td>%</td>
<td>91.6</td>
<td>91.2</td>
</tr>
<tr>
<td>Heliostat reflection</td>
<td>%</td>
<td>89.1</td>
<td>89.1</td>
</tr>
<tr>
<td>Intercept efficiency</td>
<td>%</td>
<td>96.3</td>
<td>96.0</td>
</tr>
<tr>
<td>Absorption efficiency</td>
<td>%</td>
<td>94.0</td>
<td>94.0</td>
</tr>
<tr>
<td>Thermal efficiency</td>
<td>%</td>
<td>94.65</td>
<td>94.60</td>
</tr>
<tr>
<td>Total efficiency</td>
<td>%</td>
<td>58.8</td>
<td>58.8</td>
</tr>
</tbody>
</table>
The single-point simulation comparison shown in Table 2.1 indicates excellent agreement across the range of modeled physical effects. Performance is also compared at a matrix of sun positions. The discrepancy between total optical efficiency of the solar field (DELSOL3 subtracting SolarPILOT) is shown in Figure 2.9. These results show good agreement throughout the range of sun positions, but error increases substantially at very low sun elevation angles. The reason for this disagreement is not fully clear, but possible causes include differences in shadowing and blocking calculations or potential inaccuracy in the image shape model as applied to single heliostats at severe reflection angles. Regardless, the heliostat field will not typically operate at low sun positions because of shadowing and blocking effects, and solar resource is diminished when the sun is near the horizon, so the effect of the inaccuracy is minimal on annual energy production.

Figure 2.9: The difference in calculated optical efficiency between DELSOL3 and SolarPILOT as a function of sun position for the case shown in Table 2.1. The difference shown is DELSOL fractional efficiency minus SolarPILOT fractional efficiency at each evaluated sun position.
2.5 Conclusions

A new model for calculating solar field layouts and performance characteristics for power tower systems is developed and described. The tool employs both an analytical Hermite polynomial expansion flux mapping technique and MCRT with SolTrace. SolarPILOT is intended for use as a third-party validation tool for existing private industry models, a research and screening tool, and a platform for development of new modeling or design techniques. The tool models a variety of solar field, heliostat, receiver geometries, and optical scenarios. One primary strength of SolarPILOT is its extension of the analytical flux technique from DELSOL3 onto individual heliostats. This allows a more flexible design process, including possible asymmetry, topography variation, and geometry variation within the heliostat field.

SolarPILOT has been integrated into NREL’s SAM software as the power tower design and characterization engine. This integration is via an API, and future work on the software will involve improvement to the API for general use.

2.6 Acknowledgements

Funding for this project was provided to NREL by the U.S. Department of Energy under Contract No. DE-AC36-08GO28308. The authors gratefully acknowledge our colleagues Greg Kolb (ret.) and Cliff Ho at Sandia National Laboratory in Albuquerque, New Mexico, for their contributions to DELSOL3 and guidance on the methodologies. We also thank Professors Rob Braun and Alexandra Newman in the Department of Mechanical Engineering at Colorado School of Mines for technical review of the material in this paper.
CHAPTER 3
OPTIMIZED DISPATCH IN A FIRST-PRINCIPLES CONCENTRATING SOLAR POWER PRODUCTION MODEL

A paper submitted to the journal Applied Energy

Michael J. Wagner\textsuperscript{6,7}, Alexandra Newman\textsuperscript{7,8,9}, Robert Braun\textsuperscript{7,9}, William Hamilton\textsuperscript{7,10}

3.1 Abstract

Concentrating solar power towers, which include a steam-Rankine cycle with molten salt thermal energy storage, is an emerging technology whose maximum effectiveness relies on an optimal operational and dispatch policy. Given parameters such as start-up and shut-down penalties, expected price profiles, solar availability, and system interoperability requirements, we seek a profit-maximizing solution that determines start-up and shut-down times for the power cycle and solar receiver, and the times at which to dispatch various quantities of energy over a 48-hour horizon at hourly fidelity. Our mixed-integer linear program (MIP) is subject to constraints including: (i) minimum and maximum rates of start-up and shut-down, (ii) energy balance, including energetic state of the system as a whole and its components, (iii) logical rules governing the operational modes of the power cycle and solar receiver, and (iv) operational consistency between time periods.

The novelty in our work lies in the successful integration of our dispatch optimization model into a detailed techno-economic analysis tool, specifically, the National Renewable Energy Laboratory’s System Advisor Model (SAM). The MIP produces an optimized operating strategy, historically determined via a heuristic. Using several market pricing profiles,

\textsuperscript{6}Mechanical Engineer, Ph.D., National Renewable Energy Laboratory, Golden, CO 80401
\textsuperscript{7}Department of Mechanical Engineering, Colorado School of Mines, Golden, CO 80401
\textsuperscript{8}Corresponding author
\textsuperscript{9}Professor of Mechanical Engineering
\textsuperscript{10}Ph.D. Student
we present comparative results for a system with and without dispatch optimization, indicating that dispatch optimization can improve plant profitability by 5-20% and thereby alter the economics of concentrating solar power technology. While we examine a molten salt power tower system, this analysis is equally applicable to the more mature concentrating solar parabolic trough system with storage.

3.2 Background

The ability of renewable energy to be dispatched flexibly enables significant market penetration compared to renewable energy systems that are highly variable (e.g., wind) and/or that lack associated storage systems (e.g., photovoltaics without storage). We examine one type of solar technology, Concentrating Solar Power (CSP), that manifests itself as: Parabolic Trough, Linear Fresnel, Dish Stirling, and Power Tower. The latter, and the one we address in this paper, is thought to possess the most significant potential for improvements in efficiencies and reductions in cost [5]. Concentrating solar power tower technology uses thousands of sun-tracking mirrors (heliostats) that focus on a central receiver to heat molten salt to temperatures above 565°C (1050°F). The molten salt can then be pumped to a power cycle to generate electricity or efficiently stored for use when sunlight is not available [52]. However, the economic viability and widespread implementation of CSP technologies are strongly tied to their ability to extend their diurnal operational characteristics across peak demand time periods and during periods when solar energy is curtailed due to the sun setting or cloud cover [53]. Thermal energy storage (TES) is an enabling technology which can amass the energy captured by the receiver as a reserve for dispatch at a later, more favorable time. In fact, TES integration enables CSP to be a dispatchable renewable resource whose economics are enhanced by both improved utilization of the power cycle and an ability to shift power production to better coincide with peak demands and high-value-electricity time periods [54].

High-temperature molten salt TES has been successfully implemented in CSP tower systems [55, 56] and in parabolic trough systems, the latter in an *indirect* manner through
use of an intermediate oil-to-molten salt heat exchanger. So-called direct TES systems such as the power tower technology use molten salt both as the storage medium and as the heat transfer fluid in the receiver, thereby avoiding the intermediate heat exchanger and improving system efficiency and dispatchability [13].

The maximum storage capacity of the TES system is determined during a plant design process that considers several factors including the thermal power rating of the solar field and power cycle subsystems, plant location, project economics, and the desired capacity factor, which is defined as the quotient of total annual electrical energy production and the electrical energy production should the plant operate continuously at rated power output. Thermal energy storage sizing also depends on the operational scheme. For example, a plant that intends to operate primarily during high-revenue morning or evening periods while reducing production during daylight hours requires more TES capacity than a plant with an identical capacity factor that generates power during all daylight hours. CSP plants that target dispatch during high-revenue periods operate differently than those that minimize the average cost of energy. The former relies more extensively on a carefully planned dispatch schedule that anticipates the timing and level of thermal power production in the solar field, energy consumption for receiver and plant start up, and the charge state of TES over time. Formal optimization methods can determine the dispatch profile that maximizes electricity sales revenue over a particular time horizon given a specific system configuration, expected solar resource, pricing or time-of-dispatch (TOD) schedule, and operational constraints – a process referred to as dispatch optimization.

The intelligent dispatch of stored energy can greatly enhance the value of electricity by providing firm capacity and ancillary services, and by generating electricity during time periods in which rates are especially high [57]. Dispatch optimization involves the manipulation of the timing and rate at which electricity is generated by the power cycle and captures both physical processes and time [10]. This paper presents a methodology, implementation, and publicly available tool for simulating CSP power tower systems with optimized dis-
patch. The method expands on previous work by directly incorporating formal optimization techniques into the SAM [2] simulation software, for which previous research has relied on heuristics or on optimizing dispatch using simulation output a posteriori as optimization model input. SAM assesses CSP performance, simulating renewable technologies including CSP, wind, geothermal, photovoltaic, biomass, solar hot water, and generic systems. The software is free to download and use, and the tools developed in the current work are freely available [42]. Each technology can be paired with a financial model to evaluate the economic performance of a project within particular market, incentive, and cost environments.

3.2.1 Related Work

Optimization modeling has been applied to many types of energy systems, e.g., [10] who retrofit an existing building and determine a corresponding dispatch strategy, and [58] who examine multiple objectives in optimizing stand-alone hybrid energy systems, also with the corresponding dispatch. Other authors examine only dispatch, e.g., [59], who apply a simulation model to a hybrid photovoltaic and tri-generation power system to decrease waste from excess heat, while [60] formulate an optimization model (a mixed-integer linear program, like ours) that combines both dispatchable and intermittent power, the latter as a result of a virtual plant, to maximize profits. Similarly, [61] develop an optimization model that dispatches wind, but, in contrast to the previous work, theirs focuses on minimizing active power losses in the system while constraining reactive power; the model is solved heuristically. Thorin et al. [62], [63] and [64] operate in a market environment (as does [60]), the former for a unit commitment problem, applying an exact approach (i.e., Lagrangian Relaxation) to a mixed-integer program; Cho et al. [63] optimize a combined cooling, heating, and power system to optimize the tradeoffs between system cost, energy production and emissions, and test their model on a variety of geographic sites in the U.S. with differing weather conditions; Fürsch et al. [64] examine the expansion of a power network and the corresponding dispatch strategies in Europe; using an optimization model which combines both investment and dispatch decisions, they conclude that even optimal grid extensions,
coupled with capital cost reductions for renewable technologies, leads to significantly higher overall average electricity system costs over a time horizon of three to four decades. Parisio et al. [65] use model predictive control within an optimization (mixed-integer programming) framework in which the goal is to minimize costs subject to microgrid system constraints such as capacities, minimum up- and down-times, and start-up and shut-down requirements. They test instances of their model on an experimental microgrid in Greece. Zheng et al. [66] provide a review of bio-inspired optimization of sustainable energy systems. These works examine problems similar to ours in that dispatch policies are considered, some even using the mathematical framework we use. However, none of these examines concentrating solar power in particular, with its own sets of objectives and rules. We next discuss the research specific to our technology.

Simulation is used to predict the total electrical energy production from an existing or previously designed CSP plant over its lifetime in order to evaluate the financial return on investment, the cost of energy, the environmental (mitigation) impact, or some other measure of interest. The standard method for CSP simulation requires calculation of plant behavior over a time horizon (typically, one year with one-hour time steps) [67], and it develops a picture of long-term energy production by sequentially modeling performance at relatively short time steps compared to the overall time window of interest (e.g., hourly calculations to establish lifetime metrics). CSP systems are primarily constrained by immediate concerns, such as component or subsystem operational states, conservation of mass and energy, and heat transfer, thermodynamic, or thermo-mechanical principles.

The previous dispatch approach implemented in SAM uses a simple heuristic that allows the user to specify requirements before thermal storage can be dispatched; this heuristic does not consider the expected future thermal energy production, TES charge state, or price at which electricity can be sold, but instead determines the operational state of the power cycle based on the current TES charge state and the hour of the day. The heuristic can improve plant production during high-value hours as exemplified by SAM or Guédez et al. [15], but
can ultimately decrease the utilization of the solar field throughout the year because of TES over-charge situations.

By contrast, this work adopts a formal approach by formulating the problem as a mixed-integer program (MIP) that leverages state-of-the-art modeling languages and solvers ([68, 69]) to make the solution of a mathematical problem containing thousands of variables and constraints tractable.

Madaeni et al. [7] present a simplified approach for determining an optimal dispatch profile while implementing MIP techniques. The authors use SAM to generate an hourly thermal power production profile throughout the year that is considered as fixed input to the MIP model originally outlined in [16]. This approach factors in the simulated performance of the solar field, but omits interactions between the solar field and thermal storage or the power cycle. The latter subsystems are modeled as part of a MIP that determines the TES state of charge and electricity production from the cycle. This method improves tractability by reserving the detailed model to generate fixed input while utilizing a simplified energy balance model to characterize TES charge and power cycle generation. Furthermore, Madaeni et al. employ a rolling time horizon methodology in which they consider a 48-hour time horizon, updated every 24 hours. Our work largely adopts this approach, but importantly, uses the optimized schedule to control operational decisions within SAM’s detailed simulation model, whereas the Madaeni et al. work uses the results from the MIP as the actual estimate of plant production throughout the year.

3.2.2 Goals of the current work

Dispatch optimization improves the profitability of existing or planned CSP facilities, but it is also of great interest to policymakers and researchers who seek to better understand the projected performance of CSP systems under various deployment and grid operations scenarios. However, previous work (cf. [7, 16, 57]) considers dispatchability from the perspective of grid integration in which CSP systems are designed at an energy-flow and system sizing level to assess suitability for meeting grid and market demands. The contribution of our work is
its evaluation of the relationship between optimal dispatch profiles and technology design. Accordingly, this work fills the gap between prescriptive grid-level models on the one hand that indicate desired technology performance subject to high-level operational requirements (e.g., plant start up, maximum energy generation) and descriptive performance simulations on the other hand whose primary concern is to dynamically synthesize expected plant productivity and financial return given specific component or subsystem thermo-mechanical performance expectations. SAM develops these estimates using annual “macro-simulations” that consist of thousands of sequential “micro-simulations” within a time series, and the plant behavior at any given time step may depend on the state of the system in the previous time step(s). The SAM Molten Salt Power Tower (SAM-MSPT) model is configured as illustrated in Figure 3.1.

Figure 3.1: Molten Salt Power Tower system configuration that is modeled in SAM. The system consists of a heliostat field, molten salt receiver, direct TES system, steam generation system, Rankine power cycle, and heat rejection system. (Graphic ©NREL/Al Hicks)
The MIP in SAM operates under the following assumptions: (i) solar field thermal production over time is calculated using a simplified “forecast” model and provided as a fixed input to the dispatch model, and (ii) power cycle efficiency depends linearly on thermal input to the cycle and on the ambient temperature, and these efficiency corrections can be implemented as independent terms (see Section 3.4). Dispatch optimization enables investigation of detailed plant performance issues that are too complex to be easily represented in an energy-balance MIP model. For example, the mechanical stress associated with frequent thermal cycling of power generation equipment may lead to an increase in the frequency of required maintenance [8]. A detailed model can capture these thermo-mechanical impacts when the plant control is influenced by optimized dispatch scheduling.

3.2.3 Operating Considerations

The plant dispatch schedule determines the timing and production level from the power cycle (turbine, generator, condenser, and associated equipment). During operation, the power cycle consumes stored thermal energy from the TES system. Thermal energy storage is charged using high-grade thermal energy that is generated by the solar field during daytime operation, and energy generation is affected by the optical and thermal efficiency of the solar field, by the intensity of the available solar resource, and by the operational state of the solar field. Receiver and power cycle start-up sequences are not necessarily coordinated, so both systems may operate independently with shared interest only in the energy state of the TES system. In some cases, the receiver must curtail energy generation to avoid over-charging thermal storage (thus wasting solar energy).

Before the power cycle or receiver can produce electricity or thermal energy, respectively, start-up requirements must be satisfied, including both a minimum start-up period and a minimum energy state requirement which are surrogates for temperature considerations. In the latter case, the plant equipment cools during shutdown periods and must overcome the system’s thermal inertia to begin generating steam that powers the turbine. Likewise, the receiver consumes energy as it heats up and must complete a start-up procedure before
producing useful thermal energy. Furthermore, turbine and heat exchanger equipment manufacturers limit the maximum rate of temperature increase during start-up to avoid thermal stress and mechanical failure risks. Both the energy and duration start-up requirements must be met before equipment can begin producing power. These requirements are implemented as a constraint on the maximum energy delivered for start-up during any given time period. Although the duration of start-up must last for at least a minimum number of time steps, longer start-up durations are allowed in practice based on energy availability, and the model must provide this flexibility.

Two start-up scenarios are possible for the power cycle: (i) cold start-up, which occurs when the power cycle has shut down for any period of time and seeks to restart; and (ii) hot start-up, which occurs when the power cycle has been in standby mode and seeks to restart. Cold start-up requires an additional energy contribution and incurs more component wear and tear, whereas hot start-up can happen immediately (from the perspective of the hourly model).

Standby is a mode of operation in which a small (but non-trivial) amount of thermal energy is consumed during each time period to maintain the power cycle and/or receiver equipment in a hot state, ready to quickly ramp up for electricity generation; however, no electricity is produced in standby mode. Consequently, maintaining the power cycle in standby mode is of value if multiple start-up cycles are anticipated over a relatively short time span, or if the energy penalty or ramp rate requirement for start-up is sufficiently severe to justify the small rate of energy consumption by the power cycle.

The receiver can also operate in a standby mode during cloudy periods to avoid the full start-up procedure. In standby, salt from the cold storage tank is pumped through the receiver, and the flow is diverted back into the cold tank where the fluid temperature can decay at a rate that corresponds to the thermal losses from the receiver. Finally, the model accounts for receiver shutdown energy consumption in which the heliostat field provides sufficient energy to allow the salt to drain out without freezing before the solar field ends
operation for the day. The draining procedure requires approximately fifteen minutes while sunlight is still available, and this effect is modeled as the consumption of 25% of the hourly energy used at the minimum receiver production rate.

3.3 Mathematical Formulation

The parameters, sets, variables, objective function, and constraining relationships are described in this section. The model takes the parameters and sets as given and determines values for the decision variables to maximize an objective function while adhering to the constraints. Some parameters and all variables are subscripted with time $t$, indicating the time-varying nature of the decisions.

3.3.1 Parameters and Sets

The following MIP, $(\mathcal{R})$, requires the initial operational state of the system, the collector field and receiver energy generation profile, the expected cycle conversion efficiency profile as a function of ambient temperature and thermal input, and the energy price or tariff profile (Table 3.1). (Initialization parameters used to set variable values at $t = 0$ follow variable notation and are not included here.)

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Units</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mathcal{T}$</td>
<td>Set of all time steps in the time horizon, $T =</td>
<td>\mathcal{T}</td>
</tr>
<tr>
<td>$Q^m_t$</td>
<td>kW</td>
<td>energy generated by the solar field in time $t$</td>
</tr>
<tr>
<td>$P_t$</td>
<td>¢/kW$e$-hr</td>
<td>electricity sales price in time $t$</td>
</tr>
<tr>
<td>$W^\text{net}_t$</td>
<td>kWe</td>
<td>net power production upper limit in time $t$</td>
</tr>
<tr>
<td>$W^\text{min}_t$</td>
<td>kWe</td>
<td>minimum net power production in time $t$</td>
</tr>
<tr>
<td>$\eta^c_t$</td>
<td>-</td>
<td>normalized condenser parasitic loss in time $t$</td>
</tr>
<tr>
<td>$\gamma_t$</td>
<td>-</td>
<td>exponential time weighting factor; $\Gamma^{(t)}$, where $\Gamma \approx 0.99$</td>
</tr>
<tr>
<td>$\Delta^s_t$</td>
<td>-</td>
<td>estimated fraction of time step $t$ used for receiver start-up</td>
</tr>
<tr>
<td>$\eta^\text{amb}_t$</td>
<td>-</td>
<td>cycle efficiency adjustment factor in time $t$</td>
</tr>
<tr>
<td>$\bar{P}$</td>
<td>mean sales price (¢/kW$e$-hr); $\sum_{t \in T} P_t / T$</td>
<td></td>
</tr>
<tr>
<td>$\eta_{\text{des}}$</td>
<td>-</td>
<td>cycle nominal efficiency</td>
</tr>
<tr>
<td>Symbol</td>
<td>Units</td>
<td>Description</td>
</tr>
<tr>
<td>--------</td>
<td>-------</td>
<td>-------------</td>
</tr>
<tr>
<td>( \eta^p )</td>
<td>-</td>
<td>*slope of linear approximation of power cycle performance curve</td>
</tr>
<tr>
<td>( \tau )</td>
<td>hr</td>
<td>frequency of optimization problem execution</td>
</tr>
<tr>
<td>( E^u )</td>
<td>kW·hr</td>
<td>energy storage capacity</td>
</tr>
<tr>
<td>( E^r )</td>
<td>kW·hr</td>
<td>required energy consumed to start receiver</td>
</tr>
<tr>
<td>( E^c )</td>
<td>kW·hr</td>
<td>required energy consumed to start cycle</td>
</tr>
<tr>
<td>( E^{hs} )</td>
<td>kWe-hr</td>
<td>heliostat field startup or shutdown parasitic loss</td>
</tr>
<tr>
<td>( Q^u )</td>
<td>kW</td>
<td>cycle thermal power capacity</td>
</tr>
<tr>
<td>( Q^l )</td>
<td>kW</td>
<td>minimum operational thermal power input to cycle</td>
</tr>
<tr>
<td>( W^u )</td>
<td>kW</td>
<td>cycle electric power rated capacity</td>
</tr>
<tr>
<td>( W^l )</td>
<td>kW</td>
<td>minimum electric power output from cycle</td>
</tr>
<tr>
<td>( \dot{W}^h )</td>
<td>kWe</td>
<td>heliostat field tracking parasitic loss</td>
</tr>
<tr>
<td>( W^b )</td>
<td>kW</td>
<td>power cycle standby operation parasitic load</td>
</tr>
<tr>
<td>( \dot{W}^{rsb} )</td>
<td>kWe-hr</td>
<td>tower piping heat trace parasitic loss</td>
</tr>
<tr>
<td>( Q^{ru} )</td>
<td>kW</td>
<td>allowable power per period for receiver start-up</td>
</tr>
<tr>
<td>( Q^{rt} )</td>
<td>kW</td>
<td>minimum operational thermal power delivered by receiver</td>
</tr>
<tr>
<td>( Q^{rsd} )</td>
<td>kW</td>
<td>required thermal power for receiver shut-down</td>
</tr>
<tr>
<td>( Q^{rsb} )</td>
<td>kW</td>
<td>required thermal power for receiver standby</td>
</tr>
<tr>
<td>( Q^c )</td>
<td>kW</td>
<td>allowable power per period for cycle start-up</td>
</tr>
<tr>
<td>( Q^b )</td>
<td>kW</td>
<td>standby thermal power consumption per period</td>
</tr>
<tr>
<td>( L^r )</td>
<td>kWe/kW</td>
<td>receiver pumping power per unit power produced</td>
</tr>
<tr>
<td>( L^c )</td>
<td>kWe/kWt</td>
<td>cycle Heat Transfer Fluid (HTF) pumping power per unit energy consumed</td>
</tr>
<tr>
<td>( C^{rsu} )</td>
<td>$</td>
<td>penalty for receiver start-up (from 0)</td>
</tr>
<tr>
<td>( C^{rhs} )</td>
<td>$</td>
<td>penalty for receiver start-up (from hot standby)</td>
</tr>
<tr>
<td>( C^{csu} )</td>
<td>$</td>
<td>penalty for cycle start-up (from 0)</td>
</tr>
<tr>
<td>( C^{chs} )</td>
<td>$</td>
<td>penalty for cycle start-up (from hot idle)</td>
</tr>
<tr>
<td>( \delta W^d )</td>
<td>$/kWe</td>
<td>penalty for any positive change in electricity production</td>
</tr>
<tr>
<td>( \Delta )</td>
<td>hr</td>
<td>time step duration</td>
</tr>
<tr>
<td>( \Delta^l )</td>
<td>hr</td>
<td>minimum duration of receiver start-up in period</td>
</tr>
<tr>
<td>( M )</td>
<td></td>
<td>a sufficiently large number</td>
</tr>
</tbody>
</table>

*Parameter is calculated from fixed input and discussed below.*

### 3.3.2 Variables

The variables (see Table 3.2) describe energy (thermal \( kWt - hr \) or electric \( kWe - hr \)) states and power flows (thermal \( kWt \) or electric \( kWe \)) in the system. Continuous variables “\( x \), “\( \dot{u} \), “\( u \),” and “\( s \)” representing power and energy relate to the receiver, power cycle,
and TES. Binary variables “y” enforce operational modes and sequencing such that start-up must occur before normal operation, for example.

Table 3.2: Variables used in (R).

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Units</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_t$</td>
<td>kWt</td>
<td>Cycle thermal power consumption at $t$</td>
</tr>
<tr>
<td>$\dot{w}_t$</td>
<td>kWe</td>
<td>Electrical power generation at $t$</td>
</tr>
<tr>
<td>$\dot{w}_t^\delta$</td>
<td>kWe</td>
<td>Positive change in electricity production at $t$</td>
</tr>
<tr>
<td>$x_t^r$</td>
<td>kWt</td>
<td>Thermal power delivered by the receiver at $t$</td>
</tr>
<tr>
<td>$x_t^{rsu}$</td>
<td>kWt</td>
<td>Receiver start-up power consumption at $t$</td>
</tr>
<tr>
<td>$u_t^{rsu}$</td>
<td>kWt-hr</td>
<td>Receiver start-up energy inventory at $t$</td>
</tr>
<tr>
<td>$u_t^{csu}$</td>
<td>kWt-hr</td>
<td>Cycle start-up energy inventory at $t$</td>
</tr>
<tr>
<td>$s_t$</td>
<td>kWt-hr</td>
<td>TES reserve quantity at $t$ (auxiliary variable)</td>
</tr>
<tr>
<td>$y_t^r$</td>
<td>1 if receiver is generating “usable” thermal power at time $t$; 0 otherwise</td>
<td></td>
</tr>
<tr>
<td>$y_t^{rsu}$</td>
<td>1 if receiver is starting up at time $t$; 0 otherwise</td>
<td></td>
</tr>
<tr>
<td>$y_t^{rsb}$</td>
<td>1 if receiver is in standby mode at time $t$; 0 otherwise</td>
<td></td>
</tr>
<tr>
<td>$y_t^{rsd}$</td>
<td>1 if receiver shut down at time $t$; 0 otherwise</td>
<td></td>
</tr>
<tr>
<td>$y_t^{csu}$</td>
<td>1 if cycle is starting up at time $t$; 0 otherwise</td>
<td></td>
</tr>
<tr>
<td>$y_t^{csb}$</td>
<td>1 if cycle is in standby mode at time $t$; 0 otherwise</td>
<td></td>
</tr>
<tr>
<td>$y_t^{csd}$</td>
<td>1 if cycle is shutting down at time $t$; 0 otherwise</td>
<td></td>
</tr>
<tr>
<td>$y_t^{rsup}$</td>
<td>1 if receiver is starting up at time $t$ and was not in standby mode at time $t - 1$; 0 otherwise</td>
<td></td>
</tr>
<tr>
<td>$y_t^{chsp}$</td>
<td>1 if receiver is starting up at time $t$ and was in standby mode at time $t - 1$; 0 otherwise</td>
<td></td>
</tr>
<tr>
<td>$y_t^{csup}$</td>
<td>1 if cycle is starting up at time $t$ and was not in standby mode at time $t - 1$; 0 otherwise</td>
<td></td>
</tr>
<tr>
<td>$y_t^{chsp}$</td>
<td>1 if cycle is starting up at time $t$ and was in standby mode at time $t - 1$; 0 otherwise</td>
<td></td>
</tr>
</tbody>
</table>

3.3.3 Objective Function

The objective maximizes electricity sales, which are represented as the summation over time of the product of electricity price and power generation less parasitic losses. Cost penalties associated with cycle start-up, receiver start-up, and change in electricity production between time steps are subtracted from the revenue. Binary variables $y_t^{rsd}$ and $y_t^{csd}$ introduce
a small penalty that enforces receiver and power cycle shutdown logic, respectively.

\[
(\mathcal{R}) \, \text{maximize} \sum_{t \in \mathcal{T}} \left[ \Delta \cdot P_t \left( \gamma_t y_t^\text{rsu} \cdot \dot{w}_t - L^r(x_t^r + x_t^{\text{rsu}} + Q^r y_t^{\text{rsd}}) - L^c x_t \right.ight.

\left. - \dot{W}^h y_t^r - \dot{W}^b y_t^{\text{csb}} - E^h / \Delta \cdot y_t^{\text{rsb}} - E^h / \Delta \cdot y_t^{\text{rsd}} \right)

\left. - \gamma_t (C^{\text{rsu}} y_t^{\text{rsup}} + C^{\text{rhs}} y_t^{\text{rshp}} + (E^{\text{hs}} + \Delta \dot{W}^{\text{rsb}}) y_t^{\text{rsu}})
\right.

\left. - \gamma_t (C^{\text{csu}} y_t^{\text{csup}} + C^{\text{chs}} y_t^{\text{chsp}} + y_t^{\text{rsd}} + C^c \dot{W})
\right.

\left. + \gamma_t (\bar{P} x_t^r + y_t^r) \right] \tag{3.1}
\]

3.3.4 Constraints

The relationships among the variables and parameters are established with a set of simultaneous equations and inequalities. These constraints are presented below topically with a brief description.

3.3.4.1 Receiver Operations

Receiver operations constraints include:

Receiver Start-up

\[
u_t^{\text{rsu}} \leq u_{t-1}^{\text{rsu}} + \Delta \cdot x_t^{\text{rsu}} \quad \forall t \in \mathcal{T} : t \geq 2 \tag{3.2a}
\]

\[
u_t^{\text{rsu}} \leq E^r y_t^{\text{rsu}} \quad \forall t \in \mathcal{T} \tag{3.2b}
\]

\[
y_t^r \leq \frac{y_t^{\text{rsu}}}{E^r} + y_{t-1}^r \quad \forall t \in \mathcal{T} : t \geq 2 \tag{3.2c}
\]

\[
y_t^{\text{rsu}} + y_{t-1}^r \leq 1 \quad \forall t \in \mathcal{T} : t \geq 2 \tag{3.2d}
\]

\[
x_t^{\text{rsu}} \leq Q^{\text{rsu}} y_t^{\text{rsu}} \quad \forall t \in \mathcal{T} \tag{3.2e}
\]

if \( Q_t^{\text{in}} = 0 \) then:

\[
y_t^{\text{rsu}} = 0 \quad \forall t \in \mathcal{T} \tag{3.2f}
\]

Receiver Supply and Demand

\[x_t^r + x_t^{\text{rsu}} + Q^{\text{rsd}} y_t^{\text{rsd}} \leq Q_t^{\text{in}} \quad \forall t \in \mathcal{T} \tag{3.3a}\]

\[
x_t^r \leq Q_t^{\text{in}} y_t^r \quad \forall t \in \mathcal{T} \tag{3.3b}\]

\[
x_t^r \geq Q_t^l y_t^r \quad \forall t \in \mathcal{T} \tag{3.3c}\]
if $Q^i_t = 0$ then:

$$y^r_t = 0 \quad \forall t \in T$$

(3.3d)

**Logic Governing Receiver Modes**

$$y^{rsu}_t + y^{rsb}_t \leq 1 \quad \forall t \in T$$

(3.4a)

$$y^r_t + y^{rsb}_t \leq 1 \quad \forall t \in T$$

(3.4b)

$$y^{rsb}_t \leq y^r_{t-1} + y^{rsb}_{t-1} \quad \forall t \in T : t \geq 2$$

(3.4c)

$$y^{rsup}_t \geq y^{rsu}_t - y^{rsu}_{t-1} \quad \forall t \in T : t \geq 2$$

(3.4d)

$$y^{rhaps}_t \geq y^r_t - (1 - y^{rsb}_t) \quad \forall t \in T : t \geq 2$$

(3.4e)

$$y^{rsd}_{t-1} \geq (y^{rsb}_{t-1} - y^r_t) + (y^{rsb}_t - y^{rsd}_t) \quad \forall t \in T : t \geq 2$$

(3.4f)

(\$R\$) considers receiver start-up inventory and the criteria that must be satisfied in order for it to produce useful power. Constraint (3.2a) tracks start-up energy “inventory” using an inequality, rather than an equality, to allow inventory to reset to zero in time periods following start-up completion; inventory is naturally maximized by the problem and can only be nonzero for time steps in which the receiver is starting up by Constraint (3.2b). Constraint (3.2c) allows receiver power production only after start-up has been completed or when the receiver was operating in the previous time step. Constraint (3.2d) ensures that receiver start-up mode does not persist while the receiver is operating in power-producing mode by disallowing start-up in the time step following normal power production operation. Constraint (3.2e) ensures that the actual power used for receiver start-up is no more than the ramp rate limit for each time step. Constraint (3.2f) prevents receiver start-up from occurring in time periods with trivial solar resource.

The total power produced by the receiver has an upper bound of the available energy $Q^i_t$, and any start-up or shutdown energy consumption detracts from production according to Constraint (3.3a). The receiver can only generate thermal power when it is in power-producing mode (i.e., $y^r_t = 1$) by Constraint (3.3b). Constraint (3.3c) is enforced because of molten-salt pump operating limits and heat transfer requirements in the receiver, ensuring that the receiver energy generation must satisfy a minimum threshold. Constraint (3.3d)
ensures that the receiver power-producing mode does not persist when no energy is available.

While the receiver is in standby mode, molten salt is circulated between the cold TES tank and receiver, enabling fast restart. A smaller hot start-up penalty is enforced when beginning normal operation from standby mode. Neither standby and start-up modes (Constraint (3.4a)) nor standby and power-producing modes (Constraint (3.4b)) can coincide. Standby mode can persist over time, but must follow time steps in which the receiver was either in standby or power-producing mode (Constraint (3.4c)). Constraints (3.4d) and (3.4e) enforce logic associated with incurring a penalty for receiver start-up from an off or standby state, respectively. Constraint (3.4f) enforces the logic for shut-down from a power producing or standby state. Constraint (3.10a) ensures non-negativity for receiver start-up power consumption and receiver start-up energy inventory. Non-negativity for $x_r^t$ is ensured via Constraint (3.3c). Constraint (3.10c) enforces binary requirements on the variables associated with generating usable thermal power, receiver start-up, receiver standby, receiver shut down, and receiver start-up penalties.

3.3.4.2 Power Cycle Operations

Power cycle operation constraints largely mirror those of receiver operations and include:

*Cycle Start-up*

\begin{align*}
    u^{csu}_t &\leq u^{csu}_{t-1} + \Delta \cdot Q^c y^{csu}_t & \forall t \in T : t \geq 2 \\
    u^{csu}_t &\leq M y^{csu}_t & \forall t \in T \\
    y_t &\leq \frac{u^{csu}_t}{E_c} + y_{t-1} + y^{csb}_{t-1} & \forall t \in T : t \geq 2 \\
    x_t + Q^c y^{csu}_t &\leq Q^u y_t & \forall t \in T \\
    x_t &\leq Q^u y_t & \forall t \in T \\
    x_t &\geq Q^l y_t & \forall t \in T 
\end{align*}

*Power Supply and Demand*

\begin{align*}
    \dot{w}_t &\leq \frac{\eta_{amb}^t}{\eta_{des}^t} (\eta^c x_t + y_t (W^u - \eta^c Q^u)) & \forall t \in T 
\end{align*}
\[ \dot{w}_t^d \geq \dot{w}_t - \dot{w}_{t-1} \quad \forall t \in \mathcal{T} : t \geq 2 \]  
(3.6b)

If \( \dot{W}_t^{net} \geq \dot{W}_t^{min} \) then:
\[
\dot{W}_t^{net} \geq \dot{w}_t(1 - \eta_c^t) - L^r(\alpha + \beta_{su,t}) \\
- x_t L^c - y_{tsu}^t \left( \frac{W_{rsb}^r}{\Delta} + \frac{E_{hs}^b}{\Delta} \right) \\
- \dot{W}_t^{h} \dot{y}_t^r - y_{tsb}^t \dot{W}_t^{b} \forall t \in \mathcal{T}
\]  
(3.6c)

else:
\[ \dot{w}_t = 0 \quad \forall t \in \mathcal{T} \]  
(3.6d)

**Logic Governing Cycle Modes**

\[ y_{tsu} + y_{t-1} \leq 1 \quad \forall t \in \mathcal{T} : t \geq 2 \]  
(3.7a)

\[ y_{tsb}^c \leq y_{t-1}^c + y_{t-1}^{csb} \quad \forall t \in \mathcal{T} : t \geq 2 \]  
(3.7b)

\[ y_{tsu}^c + y_{tsb}^c \leq 1 \quad \forall t \in \mathcal{T} \]  
(3.7c)

\[ y_t + y_{tsb}^c \leq 1 \quad \forall t \in \mathcal{T} \]  
(3.7d)

\[ y_{tsup} \geq y_{tsu}^c - y_{t-1}^{csu} \quad \forall t \in \mathcal{T} : t \geq 2 \]  
(3.7e)

\[ y_{tsup} \geq y_t - (1 - y_{t-1}^{csb}) \quad \forall t \in \mathcal{T} : t \geq 2 \]  
(3.7f)

\[ y_{tsad} \geq y_{t-1}^{csu} + (y_{t-1}^{csb} - y_{tsu}^c) \quad \forall t \in \mathcal{T} : t \geq 2 \]  
(3.7g)

Constraint (3.5a) tracks start-up energy inventory, and Constraint (3.5b) allows nonzero inventory only during periods of cycle start-up. Constraint (3.5c) allows normal cycle operation only when start-up has been completed, when the cycle was previously operating, or when the cycle has been in standby mode. Constraint (3.5d) limits the cycle start-up rate, and Constraint (3.5e) enforces a maximum thermal power consumption limit by the power cycle. When operating, the cycle must produce a minimum amount of power enforced by Constraint (3.5f). Constraint (3.6a) determines electrical power production based on a linear cycle performance curve and the ambient temperature efficiency. The positive change in electrical power production is determined by Constraint (3.6b). The presence of \( \dot{w}_t^d \) in the objective function provides a disincentive to vary power production from one time step to the next, thereby reducing system cycling and more closely representing operator-preferred generation profiles. The appropriate magnitude of this penalty parameter is unknown but is explored further in a sensitivity analysis provided in Section 4. Constraints (3.6c) and
(3.6d) ensure that if the net power production upper limit is greater than or equal to that of the lower limit in any given time period, then that former production level must exceed that actually produced when efficiency is accounted for, less that from parasitics due to pumping power, heliostat field start-up, heliostat field tracking, power cycle standby, and tower piping heat trace. If the net power production upper limit is less than the lower limit in any given time period, the production level is zero. Start-up mode persistence is prevented in Constraint (3.7a). Standby mode can persist according to the analogous receiver requirements (Constraint (3.7b)). Standby and start-up modes cannot coincide (Constraint (3.7c)), nor can standby and power-producing mode (Constraint (3.7d)). Constraint (3.7e) enforces the penalty logic for start-up from an off state while (3.7f) enforces the penalty logic for start-up from a standby state. Constraint (3.7g) enforces the logic for shut-down from a power-producing or standby state. Constraint (3.10b) ensures non-negativity for cycle start-up energy inventory, electrical power generation, and positive change in electricity production. Non-negativity for \( x_t \) is ensured via Constraint (3.5f). Constraint (3.10d) enforces binary restrictions.

### 3.3.4.3 Energy Balance

The energetic state of the system implicates positive and negative power terms, and the charge state of thermal storage (\( s_t \)) accounts for the cumulative difference between them. Several additional constraints regarding TES state of charge are enforced as follows:

\[
s_t - s_{t-1} = \Delta \cdot [x_t^r - (Q^c y_{t}^{csu} + Q^b y_{t}^{csb} + x_t + Q^{rsb} y_{t}^{rsb})]
\]
\[
\forall t \geq 2 \in T
\]

\[
x_{t+1} + Q^b y_{t+1}^{csb} \leq \frac{s_t}{\Delta t_{t+1}} - M \cdot (-3 + y_{t+1}^{rsu} + y_{t+1} + y_{t+1}^{csb} + y_{t+1}^{rsb})
\]
\[
\forall t \in T : t \leq T - 1
\]

Constraint (3.8a) ensures that energy into and out of TES balance with the charge state, and the conversion from power to energy introduces a time step parameter \( \Delta \). Constraint (3.8b) addresses an artifact arising from the difference between the modeling time resolution
(hourly) and the amount of time required to start the plant, which may not be in units of whole hours. If the power cycle is either running or in standby in time step \( t \) and in time step \( t + 1 \), and if the receiver starts up in time \( t + 1 \), then the minimum charge level in TES in time \( t + 1 \) must be sufficient to carry operation through the receiver start-up period. Note that \( y_t + y_{t+1}^{csb} \leq 1 \) is enforced elsewhere. Equation (3.9) determines the expected fraction of each time step that would be used for receiver start-up, if applicable.

\[
\Delta_t^{rs} = \min \left\{ 1, \max \left\{ \Delta_t, \frac{E^c}{\max \{ \epsilon, Q_{t+1}^{in} \}} \right\} \right\}
\]  

(3.9)

Constraints (3.8a)-(3.8b) only track TES state of charge based on energy flow bookkeeping, not temperature. Accounting for energy quality in the TES system via temperature of the molten salt introduces non-linear complexity and is not necessary in this formulation as previously discussed.

Variable bounds are enforced in (3.10a)-(3.10d), with (3.10b) bounding both the minimum and maximum amount of energy in storage.

\[
\begin{align*}
    x_t^r, u_t^{rsu}, u_t^{csu} & \geq 0 \quad \forall t \in \mathcal{T} \\
    x_t, w_t^{\delta}, s_t & \geq 0; \quad s_t \leq E^u \quad \forall t \in \mathcal{T} \\
    y_t^r, y_t^{rsu}, y_t^{rsup}, y_t^{rbh}, y_t^{rbd}, y_t^{rse} & \in \{0, 1\} \quad \forall t \in \mathcal{T} \\
    y_t, y_t^{csu}, y_t^{csb}, y_t^{csp}, y_t^{chsp} & \in \{0, 1\} \quad \forall t \in \mathcal{T}
\end{align*}
\]  

(3.10)

### 3.3.4.4 Cycle Part-Load Correction

An optimized dispatch profile may result in electricity production lower than the CSP plant design-point during certain time periods in order to conserve stored thermal energy for more favorable future market conditions, or to avoid penalties associated with shut-down and start-up, for example. However, power cycle efficiency is adversely affected by departure from design, as shown in Figure 3.2 [11].

The relationship between thermodynamic efficiency and thermal input is nonlinear and, consequently, poses computational challenges. In order to improve tractability in the corresponding optimization model, an approximately linear function of cycle thermal power
consumption resolves the nonlinearity $\eta^{\text{cycle}}(x_t) \cdot x_t$ by modeling electrical output, shown in Constraint (3.6a). The linear coefficient is the quotient of the difference between the minimum and maximum output from the power cycle and the corresponding expression for the thermal power input.

$$\eta^p = \frac{W^u - W^l}{Q^u - Q^l}$$ (3.11)

### 3.3.5 Dispatch Model Implementation

The typical model instance contains 912 variables and 1,615 constraints. AMPL and CPLEX presolve reductions result in a problem with an average of 442 variables and 652 constraints, and an average run time on a Dell PowerEdge R410 server running Ubuntu 14.04 with 12GB RAM, 16 Intel processors at 2.72GHz each of 0.43 seconds per 48-hour horizon evaluation. By contrast, implementation of the model using LPSolve [70], which is a freeware MIP solver platform for C++, requires an average of 0.83 seconds per solve. Presolve reductions are less effective, producing instances with 890 variables and 920 constraints.
The number of time steps in the time horizon \((T)\) must be chosen with care, as it greatly affects the typical model described here as well as system techno-economic performance. The following considerations are relevant when choosing a time horizon duration: (i) the problem complexity grows exponentially with the time horizon length, and consequently, the amount of time needed for an annual simulation will also grow significantly; (ii) the optimized dispatch profile maximizes revenue within the allotted time horizon, and an insufficiently long horizon emphasizes near-term production at the expense of future, higher-value time periods; (iii) an optimal profile may require thermal energy to be held in storage overnight, and an insufficiently long time horizon (e.g., 24 hours) will fail to account for next-day requirements; and, (iv) given limitations on the number of branch-and-bound iterations and/or computation time per solve, an increased horizon length raises the likelihood of adopting a suboptimal dispatch profile, thereby negatively affecting expected plant performance. Figure 3.3 shows the impact of the time horizon length on the annual energy production and power purchase agreement (PPA) price (discussed in the next section) for the reference plant defined in Table 3.3 below.

![Figure 3.3: The impact of time horizon length (hours) on annual energy production and PPA price.](image)
3.4 Model Implementation

Figure 3.4 illustrates the dispatch optimization model within SAM whose interface provides both input and output display. The user selects the technology and financial model, then modifies the inputs to emulate their technology configuration of interest, after which SAM simulates technical and financial performance by sending information from the interface to the SAM Simulation Core. Therein lies the molten salt power tower (SAM-MSPT) technology model that contains a solar field design algorithm called SolarPILOT and detailed calculators for determining weather data and the performance of the collector, receiver, power block, and TES subsystems.

The SAM-MSPT model simulates annual production by evaluating performance over a sequence of hourly time steps, at each of which the CSP controller determines the best operational mode given the conditions endogenous and exogenous to the system. The CSP solver ensures that all of the interconnected inputs and outputs among the calculators agree with respect to the thermodynamic state of the system. In summary, the architecture in Figure 3.4 characterizes a molten salt power tower plant with storage, in which the hour-by-hour plant operation protocol is determined using a 48-hour time horizon that rolls forward in 24-hour increments.

The Production Forecast Model determines expected future thermal energy generation of the solar field. While it is possible to implement a variety of techniques for predicting electricity pricing, ambient temperature, and direct normal irradiance, this paper uses “perfect forecasting” in which the model generates expected performance by reading ahead in the weather file. SAM-MSPT incorporates the time series data from the weather and pricing databases corresponding to the horizon over which the model is solved.

The heliostat field concentrates power on the receiver \( Q^\text{helo}_t \) according to the instantaneous optical efficiency \( \eta_t^{sf} \), direct normal irradiance \( d_t \), and mirror area \( A^{sf} \).

\[
Q^\text{helo}_t = \eta_t^{sf} d_t A^{sf}
\]  

(3.12)
Figure 3.4: Information flow in the SAM-MSPT model. The MIP formulation is solved as a simultaneous set of equalities and inequalities, and the hourly solution profile is used by the CSP Controller to set target power production levels and operational states over the subsequent operational time horizon.

The total expected solar field production is the nonnegative difference of incident power on the receiver and convective \( Q_{t}^{\text{conv}} \) and radiative \( Q_{t}^{\text{rad}} \) thermal losses:

\[
Q_{t}^{\text{in}} = \max \left[ 0, Q_{t}^{\text{helio}} - Q_{t}^{\text{conv}} - Q_{t}^{\text{rad}} \right] \quad \forall t \in T
\]  

(3.13)

The following reduced-order relationships model the expected technical performance of the collector and receiver, providing a reasonably accurate approximation of expected field productivity. The collector field model generates a lookup table containing optical efficiency as a function of sun position, and the CSP controller supplies this information to the forecast model. The complexity of modeling the receiver thermal loss via convection and radiation from the heated surface necessitates a simplified forecasting model: an area-weighted average
molten salt temperature is given as the weighted average of the inlet and outlet temperatures, where the coefficient is receiver-specific [9].

\[ T_{eff} = 0.55 \cdot (T_{out} + T_{in}) \]  

(3.14)

Radiative losses are calculated at each time \( t \) as:

\[ Q_{rad}^t = A_{rec} \sigma \epsilon \left( \left( T_{eff}^t \right)^4 - \left( T_{amb}^t \right)^4 \right) \]  

(3.15)

in which \( A_{rec} \) is the receiver surface area, \( \sigma \) is the Stefan-Boltzmann constant, \( \epsilon \) is the temperature-weighted surface emittance, and \( T_{amb}^t \) is the expected ambient dry-bulb temperature. Convective losses are expressed as a function of wind velocity for the molten salt technology, scaled by radiative loss. The coefficients in (3.16) are determined by regressing simulated data points that are generated using the SAM-MSPT detailed receiver model.

\[ Q_{conv}^t = \left( -5.645 \times 10^{-4} V_t^3 + 0.01561 V_t^2 \\
- 0.00911 V_t + 0.48124 \right) Q_{rad}^t \]  

(3.16)

where \( V_t \) is the wind velocity at time \( t \).

The Engineering Performance Model (consisting of the CSP controller, CSP solver, and detailed performance calculators in Figure 3.4) predicts plant behavior and productivity over time using computationally expensive procedures derived from physically based, first-principles modeling of thermodynamics and heat transfer phenomena. The model’s engineering performance behavior is validated and discussed in detail in [11] and [12].

The MIP Mathematical Formulation, when solved with an appropriate algorithm, determines the performance and operation of the plant using the forecast model and various operational constraints (see Section 3.3).

The Pricing Model calculates the PPA price, which is the minimum value at which a power producer should agree to sell electricity in order to ensure that a specified internal rate of return is achieved. The PPA price is a useful surrogate for the profitability of a project in that it accounts for the variability in electricity value with time of day and time of year.
As it is applied in SAM, the PPA price is multiplied by the hour-by-hour TOD or “tariff” rate to determine the value of electricity generated by the plant over time. SAM calculates the PPA price assuming a target internal rate of return (11% in the current study) and an annual escalation rate of 1%. For this reason – and somewhat counter-intuitively – a low PPA price is desirable. From the perspective of a power producer, a low PPA price improves its competitiveness. Alternatively, the PPA price could be specified and the internal rate of return maximized, and results from either approach would be equivalent. Our results translate the objective function value of ($\mathcal{R}$) into PPA price by taking fixed costs as sunk and maximizing revenue generated from electricity sales.

3.5 Case Studies

This study explores a range of plant TES sizes and solar multiples, the latter of which is defined as the ratio of solar field thermal power output to power cycle thermal input at design conditions. As the solar multiple increases, so too does the optimal amount of TES and the resulting plant capacity factor, but these values may be chosen independently. Table 3.3 provides a summary of key design parameters which are obtained from the default SAM-MSPT case. For this analysis, SAM automatically determines the heliostat field layout given the specified solar multiple and other design parameters. Each evaluation takes as fixed the TES and solar multiple and determines the optimal dispatch schedule for that system configuration.

In addition, this analysis considers four market scenarios (Figure 3.5), three of which have been adopted from Guédez et al., and one of which is the “generic summer peak” scenario used as the default for the SAM-MSPT model. The two-tier tariff market encourages daytime production with an evening spike. The pool price tariff introduces an additional morning spike and weights incentives seasonally. The fixed daytime tariff allows sales during daytime hours, but is unique in its binary nature; no revenue is available during nighttime operation. Finally, the SAM generic peak schedule combines features from the two-tier and pool price tariffs.
Table 3.3: Case study plant design and control parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Units</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gross electrical output</td>
<td>MWe</td>
<td>115</td>
</tr>
<tr>
<td>Cycle design efficiency</td>
<td>%</td>
<td>41.2</td>
</tr>
<tr>
<td>Cycle design thermal input</td>
<td>MWt</td>
<td>278.1</td>
</tr>
<tr>
<td>Cycle maximum output</td>
<td>MWe</td>
<td>120.75</td>
</tr>
<tr>
<td>Cycle minimum output</td>
<td>MWe</td>
<td>28.75</td>
</tr>
<tr>
<td>Cycle start-up energy</td>
<td>MWt-hr</td>
<td>57.5</td>
</tr>
<tr>
<td>Cycle start-up time</td>
<td>hr</td>
<td>0.5</td>
</tr>
<tr>
<td>Cycle standby consumption</td>
<td>MWt</td>
<td>23</td>
</tr>
<tr>
<td>Receiver max. output (relative*)</td>
<td>-</td>
<td>1.2</td>
</tr>
<tr>
<td>Receiver min. output (relative)</td>
<td>-</td>
<td>0.25</td>
</tr>
<tr>
<td>Receiver start-up energy (relative)</td>
<td>-</td>
<td>0.25</td>
</tr>
<tr>
<td>Receiver start-up time (relative)</td>
<td>-</td>
<td>0.2</td>
</tr>
<tr>
<td>Receiver HTF temperature</td>
<td>ºC</td>
<td>574</td>
</tr>
<tr>
<td>Heat rejection technology</td>
<td></td>
<td>Air cooled</td>
</tr>
<tr>
<td>Heliostat size</td>
<td>m²</td>
<td>144.4</td>
</tr>
<tr>
<td>Maximum receiver flux</td>
<td>kW/m²</td>
<td>1,000</td>
</tr>
<tr>
<td>Hours of TES</td>
<td>hr</td>
<td>1, . . . , 18</td>
</tr>
<tr>
<td>Solar multiple</td>
<td>-</td>
<td>0.8, . . . , 3</td>
</tr>
</tbody>
</table>

*Relative to receiver thermal input design point.

Using SAM-MSPT, we compare the dispatch optimization methodology to the previous approach that relies on heuristic control which was configured to allow power generation any time the TES state of charge exceeded the threshold for minimum power cycle operation (satisfying Constraint (3.5f)). The cycle generates power at the design-point level unless insufficient energy is available in storage. Power cycle start-up occurs whenever energy in storage exceeds the quantity needed to deliver the start-up power for a single time period. The heuristic allows power generation until energy storage is exhausted each night, if applicable. This approach emphasizes maximum energy generation throughout the year.

3.5.1 Results

Table 3.4 presents the results of the PPA analysis, where the reported values correspond to the configuration with the minimum PPA price for the indicated scenario. Dispatch optimization successfully reduces PPA price compared to the heuristic dispatch method.
Heavily weighted schedules (i.e., pool price and two-tier) lead to more substantial PPA price reductions (about 10-15%), indicating that dispatch optimization is an essential aspect of plant operation for "peaker" markets that provide relatively short time windows of high-value energy pricing. The reader can also observe that systems operating in markets with more uniform tariff factors still benefit significantly from dispatch optimization, which alters the size of TES and the solar multiple at which PPA price is minimized. This implies that dispatch optimization should not be relegated to operational analyses, but rather should be part of the project screening and design process.

An important feature of dispatch optimization is the apparent improvement in the consistency of production during high-value time periods. Figure 3.6 illustrates this behavior for the pool price tariff scenario. Figures 3.6(a) and 3.6(b) show the hourly TES charge state...
Table 3.4: Characteristics for each market scenario in which PPA price is at a minimum value, both for heuristic (H) and optimized (O) dispatch.

<table>
<thead>
<tr>
<th>Market scenario</th>
<th>Solar mult.</th>
<th>Hours TES</th>
<th>PPA price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H</td>
<td>O</td>
<td>H</td>
</tr>
<tr>
<td>Two-tier</td>
<td>2.2</td>
<td>2.0</td>
<td>5</td>
</tr>
<tr>
<td>Pool price</td>
<td>2.2</td>
<td>2.2</td>
<td>8</td>
</tr>
<tr>
<td>Fixed daytime</td>
<td>1.8</td>
<td>2.0</td>
<td>4</td>
</tr>
<tr>
<td>SAM default</td>
<td>2.6</td>
<td>2.6</td>
<td>12</td>
</tr>
</tbody>
</table>

profiles for each day of the year for both heuristic and optimized dispatch, respectively. Also shown on the plot are the tariff multiplier schedules for summer (red) and winter (blue) that determine the revenue associated with generation during a particular hour of the day.

Dispatch optimization substantially changes the daily operational profile. Whereas heuristic dispatch allows TES to discharge in the evening and late-night hours, optimized dispatch typically reserves some quantity of TES to allow morning start-up. The TES profiles show that heuristic dispatch is much more operationally repetitive relative to optimized dispatch, implying that the latter strategy accounts for expected resource availability and future pricing when scheduling TES usage.

Figures 3.6(c) and 3.6(d) show the distribution of electricity generation for each hour of the day over the course of the year. Each box-whisker plot describes the variability in electricity generation for each day at the specified hour, and the box limits indicate the extents of the first and third quartiles. The whiskers correspond to twice the inner quartile range. Points that lie outside of this limit are plotted individually and are distribution outliers.

Figure 3.6(c) shows that heuristic electricity production is highly variable in the early morning, evening, and nighttime hours (tall boxes) and is less variable during daytime hours (short boxes). The variability in electricity generation is inversely related to solar resource availability – an intuitive observation. However, production is highly variable during peak revenue hours as shown by the tariff multipliers. Figure 3.6(d) depicts optimized dispatch.
in which electricity generation variability is reduced during peak revenue hours.

(a) Daily thermal storage charge state profile - heuristic dispatch

(b) Daily thermal storage charge state profile - optimized dispatch

(c) Annual variability of electricity generation - heuristic dispatch

(d) Annual variability of electricity generation - optimized dispatch

Figure 3.6: Comparison of performance profiles for the pool price tariff schedule. Plots (a) and (b) show traces of the TES charge state for each day of the year. Plots (c) and (d) show box-whisker plots of daily electricity production variability over a year grouped by hour of the day. Each box indicates the mean annual electricity generation by hour, the first and third quartile limits (box limits), and two times the interquartile range (whiskers). “Outliers” are shown as blue dots. Summer (red) and winter (blue) tariff multipliers are overlaid on each plot.

3.5.2 Penalty Parameter Sensitivity Study

Our study also seeks to understand the impact of operational cost parameters on both the generation profile and on PPA price. Plant operation that requires multiple daily start-ups or frequent production ramping may be difficult to execute and lead to additional maintenance
costs over time. We quantify the revenue and production impact of obtaining “desirable” operational profiles (that is, relatively consistent output with few starts or ramp events).

The production change penalty, $C_{\delta W}$, penalizes any positive change in power cycle electricity production from one hour to the next. Figure 3.7 presents the dispatch profile over several selected days in September in which four different penalty values are used. As the value of $C_{\delta W}$ increases, the optimal solution sacrifices maximizing generation during periods of peak revenue and cycle efficiency to improve output stability. If increased to an extreme ($C_{\delta W} = 10.0$), the dispatch profile approaches that of a baseload plant, only peaking for very short periods of time.

![Figure 3.7: Plant power generation profile with varying change in production penalty values, $C_{\delta W}$. (Penalties are given in the legend.)](image)

---

74
This analysis leads to several considerations regarding the optimal design of a CSP plant given the potential ramping costs of the cycle. Namely, if production change costs truly are on the order of 10$/\Delta kW\cdot h$, then the solar multiple, thermal storage, and power cycle sizes should generally be chosen to mimic a baseload plant. Penalties for frequent production changes would only be offset for the case in which TOD pricing variations are very large. Furthermore, an operator might reduce dispatch profile complexity but at some expense to apparent near-term plant profitability.

We also consider two TOD pricing scenarios ("Default" and "Peaker") in which the hours of TES and solar multiple are optimized for the no-penalty case. The first scenario is the generic summer peak profile in SAM, and the second is the pool price profile with spikes in pricing in the morning and evening and a price reduction during the middle of the day.

Figure 3.8 shows the impact of increasing the production change cost penalty on annual energy generation, PPA price, and number of turbine cycles per day, which is calculated as the total annual positive change in cycle production normalized to a value that corresponds to ramping the cycle from off to full load once a day for the entire year. If the number of cycles per day is greater than unity, then the turbine experiences more than one full cycle per day on average.

Several interesting observations arise from this analysis. First, the number of cycles per day decreases as the production change cost penalty increases, as intended. If production variability is not penalized at all, the optimal solution results in more than one cycle on average per day for both the Default and Peaker cases. As the penalty for changing production increases, the number of cycles drops significantly, which may be an important factor in increasing plant lifetime and reducing maintenance costs. Remarkably, the number of cycles can be reduced by 50% or more by manipulating this penalty without significant degradation of the objective function value.

Second, the trends in reduction of cycles per day, annual energy generation, and PPA price are mirrored between the Default and Peaker cases. Both show that production change
cost in the range of 0.5-2.0 $/kWe minimizes PPA price and number of cycles per day, though
the true costs of turbine ramping are not known and thus omitted from the PPA calculation.
Non-coincidence of this outcome may imply an important cost threshold regarding CSP
plants in general. Lastly, increasing the penalty leads to reduced annual output and increased
PPA price below a threshold corresponding to 0.4-0.6 cycles per day.

A final study considers the cycle start-up cost penalty’s impact on the same performance
metrics. This penalty is related to ramping cost, but differs in that it represents a penalty
incurred for a discrete event that occurs only when the power cycle transitions from an off
state to an on state, after which this penalty does not influence operation. Figure 3.9 shows
the result of varying start-up cost for the Default case.

As with the production change penalty, the start-up penalty can significantly affect the
behavior of the power cycle. A small cost of $100 per start leads to a relatively large
annual number of cycle starts (about 250). As a point of comparison, the number of cycle
starts incurred using heuristic dispatch is 370 per year. The number of starts remains
fairly constant (within variance that is to be expected based on numerical error in the
solution) until the cost increases by a factor of 100, and a factor increase of 1,000 reduces
starts by approximately 50% without a significant effect on annual energy output and PPA
price. Therefore, operational protocols that seek to minimize full cycle starts and stops
can theoretically offer equally viable financial performance compared to more traditional
approaches.

3.5.3 Applications

Results heretofore shown are readily applicable in practice, both for modeling and plant
operations applications. First, modeling activities are fundamental to research, project de-
velopment, and policymaking decisions, and an accurate estimate of technology performance
directly impacts each of these areas. Researchers require tools that quantify the impact of
advances in the technology, and utilize models to identify research priorities. The provision
of a dispatch optimization tool in a publicly available software package enables assessment
Figure 3.8: Impact of production change cost penalty on number of turbine cycles per day, annual energy generation, and PPA price for two pricing scenarios – a generic summer afternoon peak schedule (Default) and a morning/evening double-peak (Peaker) schedule. Annual energy and PPA price are shown as fractional values relative to the lowest-penalty case.

of the value of new thermal energy storage technologies – e.g., [71], or power cycles – e.g., [72], that otherwise may not interact with other subsystems as anticipated upon deployment. Project developers rely on models for initial plant design, attaining financing, project permitting, and finally, during plant operation. Dispatch optimization tools such as this are valuable for these purposes, and the authors present additional applied results and model validation in [73].
Figure 3.9: Number of cycle starts per year, annual energy output, and PPA price for the Default case with varying scenarios for cycle start-up cost.

3.6 Conclusions

We develop and implement a mixed-integer programming model within SAM to optimize the TES dispatch schedule for a molten salt power tower plant; this schedule provides a target power generation profile that is used in conjunction with a simulation model that evaluates plant performance at an hourly level over a year-long time horizon. SAM’s detailed performance model mitigates some of the approximations present in the MIP formulation.

The results indicate that dispatch optimization can significantly improve plant revenue, though the gains vary with plant capacity factor and electricity markets; scenarios with heavily weighted pricing schemes or narrow windows of high revenue benefit the most, e.g.,
PPA price – indicative of the profitability of the plant – in these cases can improve by 10-15%. Plant revenue is negatively affected by the energetic and financial cost of starting the solar receiver and power cycle equipment, and this paper shows that optimized generation profiles can achieve a reduction in the number of turbine starts per year of 50% or more – in some circumstances – with little impact on project financial performance.

In summary, our model provides a methodology to optimize the trade-offs between component and subsystem performance, the effects of demand, and the amount of revenue obtained under various market schedules. Future work will incorporate, inter alia, forecast uncertainty, and more precise cost estimates of component operations and maintenance requirements. It will also examine how plant design and maintenance affect the overall cost and nature of the dispatch strategy.
CHAPTER 4
DISPATCHING POWER AT A CONCENTRATING SOLAR ENERGY FACILITY

A paper to be submitted to the journal *Interfaces*

Michael J. Wagner\textsuperscript{11,14}, Alexandra Newman\textsuperscript{12,13,14}, Robert Braun\textsuperscript{13,14}, Jolyon Dent\textsuperscript{15}

4.1 Abstract

Concentrating Solar Power (CSP) generates electricity by reflecting the sun’s rays from a vast expanse of mirrors onto a tower, where it is absorbed as thermal energy, and either dispatched for generation of electric power or stored for future use. CSP systems differ from more commonplace photovoltaic technologies, employing a sophisticated receiver, power cycle, and a “heliostat field” comprised of thousands of mirrors spread over hundreds of acres of land. Whereas photovoltaics may be used across a wide range of scales – e.g., to supplement energy demand for a house, the technology is not currently accompanied by a low-cost energy storage mechanism. By contrast, CSP systems are most cost-effective at large scale and with relatively large quantities of energy storage which can be scheduled for dispatch using a variety of methods. For this reason, CSP is poised to become an essential component of the United States’ dispatchable renewable energy production portfolio. We present a mixed integer programming model to determine a maximum-revenue dispatch strategy over a 24-hour time horizon at hourly fidelity, taking into consideration system configuration and interoperability aspects such as storage tank size, production capacities, and ramp rates. We apply our model to a concentrated solar power plant under development in California, and owned by SolarReserve with a goal of improving modeled operability and net lifetime revenue such that financing, permitting, and design optimization processes are expedited in the near

\textsuperscript{11}Mechanical Engineer, Ph.D., National Renewable Energy Laboratory, Golden, CO 80401

\textsuperscript{12}Corresponding author

\textsuperscript{13}Professor of Mechanical Engineering

\textsuperscript{14}Department of Mechanical Engineering, Colorado School of Mines, Golden, CO 80401

\textsuperscript{15}Financial and Performance Analysis, SolarReserve, Santa Monica, CA 90401
Publicly available software contains the methodology that optimizes the dispatch using simulating performance inputs from detailed engineering models. The improved approach yields an approximately $200M reduction in expected lifetime maintenance costs, and reduces the number of power cycle start-up events by two thirds.

4.2 Introduction

Concentrating Solar Power (CSP), although relatively less common than photovoltaics, legendarily originates with Archimedes who destroyed the Roman fleet in 212 B.C. with “burning glass” [74]. The modern rendition concentrates the sun’s rays onto a flux-absorbing receiver atop a tall tower using thousands of ray-collecting mirrors (“heliostats”) spread over hundreds or thousands of acres of land. The energy is transported from the receiver to a thermal energy storage (TES) system via a heat transfer fluid. Stored energy can be utilized to power a thermodynamic conversion cycle – typically using an expansion-turbine loop, but alternative CSP technologies can also utilize heat to reform fuel, provide process heat, or augment fossil plant heat sources. The most common CSP conversion systems generate electricity using conventional steam turbines in a Rankine cycle, though power cycles using supercritical carbon dioxide (s-CO$_2$) may represent the most promising path forward [75, 76]. Because output is renewable and can be dispatched flexibly, CSP offers a linchpin technology within the United States’ production portfolio that enables significantly deeper market penetration for other cost-competitive, but more variable, renewables such as wind- and solar photovoltaic-only systems [1].

Although so-called “power tower” systems can achieve capacity factors approaching base-load status (for example, the Gemasolar facility in Fuentes de Andalucía, Spain [9]), US market structures often preferentially value energy production during peak demand hours of the day. Hence, cost-effective solutions typically operate diurnally with potential for multiple, daily production cycles. Because the lifetime of power generation equipment is highly sensitive to heating and cooling rates, cycle startup and grid synchronization typically requires between one and three hours, depending on the extent to which equipment has cooled
Among the four major CSP technologies – parabolic trough, linear Fresnel, dish Stirling, and power tower – the lattermost (also called a “Central Receiver” system and illustrated in Figure 4.1) has greatest potential for efficiency improvement and cost reduction [5]. The first US commercial power towers are only recently coming online with BrightSource™’s Ivanpah I-III and SolarReserve™’s Crescent Dunes facilities (Figure 4.2) and represent an important step for CSP in the United States, but the relative scarcity of power tower facilities worldwide leaves a dearth of publicly available knowledge on O&M costs, performance impacts, and operating strategies to minimize cost of energy.

Power tower technology with TES enjoys several important advantages over renewable and fossil alternatives, but certain challenges must be addressed to accelerate widespread commercial deployment. Advantages entail: (i) employment of TES whereby heat transfer media can be stored in an insulated high-temperature tank system with round-trip efficiency greater than 99% [7]; (ii) dispatch of power on-demand using TES, providing reliable power at
night, during cloudy periods, or during hours with high demand; (iii) achievement of higher
working temperature – and thereby conversion efficiency – of thermal energy to electricity
than other CSP technologies; (iv) reduction or absence of significant emissions of greenhouse
gases; and (v) land use per unit energy output that is similar to or less than large-scale
photovoltaic plants [77]. On the other hand, disadvantages at the time of this writing consist
of: (i) variable resource availability and forecast uncertainty; (ii) diurnal thermal cycling
as the plant starts and ends operation in order to be cost effective; (iii) high frequency
of required power block maintenance; and (iv) a significant cost owing to heliostat field
equipment which must be cleaned and is potentially subject to optical and mechanical failure
over the plant lifetime [78]. On the whole, power towers with TES are technologically
viable, but additional reductions in capital, operations, and maintenance costs are required
to compete in U.S. markets where carbon dioxide emissions are not penalized.

Figure 4.2: SolarReserve’s Crescent Dunes facility.

Optimal utilization of the TES resource is complex and multi-faceted: among other
uses, thermal energy may be (i) dispatched to produce electricity immediately upon first
availability, (ii) reserved for peak periods later in the same day or during the next day at risk of filling storage and dumping energy, or (iii) a portion can be reserved to maintain equipment temperatures, reducing power cycle startup time. Many possible dispatch permutations variously emphasize peak power production, operation through transient states of the power and receiver cycle, and expediting daily startup. The best operation strategy can change day-to-day throughout the year, depending on the weather and market pricing forecasts. Careful energy system design and dispatch can reduce costs, e.g., for an appropriately retrofitted building relative to reliance solely on the grid [79]. Rather than performing an expensive retrofit, a more cost-effective and, indeed, imperative, approach given current market competition for low-cost energy systems calls for an immediate, structured optimization effort regarding CSP. To this end, we report on a cost-minimizing dispatch strategy for a concentrated solar power facility under development near the abandoned township of Rice, California, which we refer to hereafter as “Rice.”

The model takes as inputs economic data such as the price of electricity and penalties associated with the way in which the plant and receiver are operating, and data regarding the operating characteristics of the plant and storage device, and determines an operating strategy for both the plant and receiver. The model is subject to constraints on the physical characteristics of the plant and receiver, as well as their interoperability. We show how the dispatch strategy greatly enhances the efficiency of the operation.

The remainder of the paper is organized as follows: the next section provides a literature review both on the background of our technology and on the application of dispatch policies for related technologies. We next present a qualitative description of the model, followed by its results and a corresponding analysis comparing our optimization tool with one used previously by SolarReserve, and to the heuristic dispatch method that the novel approach replaces in our engineering performance model. We conclude with a summary and extensions of our work. The detailed mathematical model can be found in the Appendix.
4.3 Literature Review

There exist a variety of applications that optimize energy operations. In terms of conventional sources, [80] examines Peoples Gas Light and Coke Company, which operates in Chicago. Their optimization model considers the uncertainty surrounding weather and, hence, demand, for natural gas. Deregulation of the associated market has prompted the model to be used to restructure supply portfolios; savings are estimated annually in the tens of millions of dollars. Mexico’s power system operator has also developed a mixed-integer programming model to dispatch gas, coal-fired, and combined-cycle plants; this model has improved management of infrastructure such as power stations and transmission lines; savings estimates are on the order of several million dollars annually [81]. Tampa Electric Company, a smaller operation than the two previously described, concerns itself with environmental regulations, which it meets via fuel blending. The associated mixed-integer program treats the supply chain in a comprehensive manner to reflect the intertwined nature of procurement, transportation, blending, and use decisions associated with its fuel [82]; savings amount to millions of dollars annually in fuel costs.

Xue et al. [83] provides an example of an application one step removed from these dispatch models; this one manages resource planning for the largest oil and natural gas producer in China. Their two-stage optimization model circumvents nonlinearities by first estimating physical parameters such as pipeline dimensions and network topology and then solving for the gas pressures and flows; the procedure iterates until convergence. Profits for long-term plans spanning several years or more are expected to increase by billions of dollars when determined via optimization, as opposed to the traditionally used manual methods.

Some authors are also concerned with maintenance plans for electric utilities. Specifically, [84] propose a preemptive maintenance and repair plan for the world’s oldest and largest underground electrical system, Consolidated Edison Company of New York. A significant impact is seen regarding safety, operating costs, and reliability of electrical service. So and Wu [85] provides a variant on maintenance planning with another proactive approach for
ensuring that energy systems yield their expected output: the authors examine optimal sampling plans to verify the efficacy of residential customer energy-efficient installations, and to provide the corresponding pricing incentives for said installations.

There has also been work done in the renewable arena. For example, both Hu et al. [86] and Johnson et al. [87] address hydrothermal scheduling in the United States, the former in the Pacific Northwest over a ten-day horizon and the latter in the Bay Area over a weekly horizon. In addition to hydro-scheduling, both models consider a mix of power technologies, primarily other renewables in the former case, while the latter considers other sources as well. Both applications estimate savings of tens of millions of dollars annually, in the former case, resulting from the consideration of stochasticity along with multiple necessary management criteria (e.g., safe dam operation, recreational use around the dam); in the latter case, the model lends credibility to a decentralized decision-making framework. Batstone et al. [88] develops a stochastic dynamic program to test an expanded electrical power network in New Zealand; of critical importance is the treatment of water storage levels for hydropower. The model enabled implementation of the expansion with minimal disruptions to the existing power network.

Our work also presents an optimization model for dispatch, but for a relatively new technology. As such, we must consider operational characteristics unique to our technology. We build upon tools created specifically for concentrated solar power. For example, the National Renewable Energy Lab develops software tools for determining subsystem design and performance (e.g., SolarPILOT™) and for predicting the productivity of the integrated power plant over the course of a year using measured weather data (e.g., System Advisor Model (SAM), [6]), which accurately and quickly quantify the impact of design and operational decisions. SolarPILOT is capable of evaluating the tradeoff between heliostat cost and optical performance, the impact of mirror soiling and washing schedules, and of selecting solar field designs that minimize the expected cost of energy. It is available as a stand-alone software package and is utilized via an application programming interface as the optical mod-
ling engine in SAM, which used to predict total plant and subsystem productivity, detailed component behavior, and financial metrics for a variety of renewable energy technologies. SAM’s CSP technology performance models are derived from a combination of engineering physical principles and semi-empirical or empirical correlations. The SAM molten salt power tower model [11] utilizes a streamlined version of the SolarPILOT optical modeling engine and detailed thermal models of the receiver, thermal storage, and power cycle subsystems. Both of these pieces of software provide the inputs to our optimization model, and allow for the integration of our dispatch optimization model, which replaces an older and less sophisticated dispatch heuristic. Furthermore, our model is implemented in SAM directly to provide a revenue-maximizing plant control scheme that the software attempts to follow as it models performance over time.

Madaeni et al. [7] present a simplified approach for determining an optimal dispatch profile while implementing mixed-integer programming (MIP) techniques. The authors use SAM to generate an hourly thermal power production profile throughout the year that is considered as fixed input to the MIP model originally outlined in [16]. This approach factors in the performance of the solar field over time, but omits interactions between the solar field and thermal storage or the power cycle. The latter subsystems are modeled as part of a MIP that determines the TES state of charge and electricity production from the cycle. This method improves tractability by reserving the detailed model for generation of fixed input while utilizing a simplified energy balance model to characterize TES charge and power cycle generation. Furthermore, Madaeni et al. employ a rolling time horizon methodology in which they consider a 48-hour time horizon, updated every 24 hours. Our work largely adopts this approach, but importantly, uses the optimized schedule to control operational decisions within SAM’s detailed performance model, whereas the Madaeni et al. work uses the results from the MIP as the actual estimate of plant production throughout the year.
4.4 Current Dispatch Model

SolarReserve™ develops and operates CSP molten salt power tower facilities both in the U.S. and internationally, including the Crescent Dunes facility near Tonopah, NV, which came online in 2016 and represents the largest power tower facility with thermal storage in the world. Various developers – including SolarReserve – target deployment of power tower systems within electricity markets that incentivize production during a subset of high-value time periods. The California Independent System Operator (CAISO) oversees one such market in which the price obtained by a power producer varies on an hourly schedule and depends on demand, transmission constraints, and interconnection location. The Rice project under development by SolarReserve is located within the CAISO operating region approximately 40 miles southwest of Lake Havasu City, AZ. Although the project has not yet been constructed, it is emblematic of SolarReserve’s technology and of the market conditions under which future plants may be built. Consequently, analysis of the facility’s expected performance and responsiveness to dispatch optimization is instructive with respect to both existing and other future projects, and production modeling is critical to a technology developer’s ability to market their product and tender competitive bids. With this motivation, we apply our dispatch optimization model to Rice.

The long-term output of a CSP plant is predicted using a deterministic simulation model at hourly intervals using expected or typical weather data – referred to as a “typical meteorological year.” A simulation consists of the sequential evaluation of plant performance at each time step for the entire year (or more). The operational state of each subsystem is determined within the model at each time step based on concurrent weather data, the energetic and operational state from the previous time step, the performance of interconnected subsystems, and the modeled plant control signal. The system sizing and component geometries are fixed with respect to time for the purposes of techno-economic modeling, and only operational parameters such as timing and rate of electricity generation and operational state of the solar field are decision variables. The outcomes from simulation are distinct from
the *in situ* application but of no less importance; operational policies are demonstrated via modeling to improve the competitive position of CSP projects, facilitating financing and design optimization processes. Therefore, it is important that the simulation both show both maximization of economic return and maintain fidelity to validated models.

We briefly digress to formally define the term “simulation,” as it retains multiple incompatible definitions depending on the reader’s primary discipline. In our usage, simulation refers to the process of constructing a model of a physical system whose behavior is sufficiently complex to preclude characterization with a closed-form or analytical solution, then executing the model over a time series in which boundary conditions also vary with time. This definition stands in contrast with common usage in operations research, in which simulation involves representation of a real system with a stochastic model, then performing sampling experiments upon the model [89]. The time-series nature of the simulation is also not to be confused with statistical time-series models in which characteristics or structures are extracted from temporally related data. Instead, we emphasize that our simulations are deterministic, predictive, and attempt to replicate time-dependent processes in a physical system via an approximate computer model.

Furthermore, we incorporate two different temporally-sensitive models. The first is the detailed engineering model (SAM, discussed previously) that relies on thermodynamic differential equations that have dimensionality in time (i.e., that model transience in the system). This is the model that is simulated, and the relevant time horizon is typically one year at hourly intervals. The second is the MIP model that we present below, which accounts for the energetic state of the system (e.g., TES charge state) but considers operational decision variables to be independent in time. This model is solved as a monolith via MIP solvers such as CPLEX and whose solution defines an optimal dispatch profile over a time horizon, which is typically a rolling horizon of 48 hours. As the simulation proceeds using the first model, the second (MIP) is periodically solved to identify the optimal dispatch profile for the upcoming hours, providing a production schedule that the first model attempts to replicate.
The optimized dispatch profile replaces a “greedy” heuristic approach in which the target maximizes production (in its simplest manifestation), such that the power cycle produces power if any thermal energy is available.

Several different strategies are available for optimizing dispatch, including those mentioned in the Literature Review Section or in [15], for example. One approach used by SolarReserve for determining optimized dispatch utilizes a Production Scheduler (PS) algorithm which seeks to identify and allocate dispatch to hours of particularly high revenue. Like other dispatch optimization techniques, the production scheduler algorithm achieves a significant improvement over heuristic methods by (i) holding stored thermal energy until it can be used to generate higher-value power, (ii) making operational decisions based on the expected price of electricity and plant performance during a particular time period rather than on the current energetic state of the system alone, (iii) generating power up to the maximum net electricity output limit, rather than producing a varying power output level that depends on the operating state of each plant subsystem; in other words, operators can account for the energy consumption of various subsystems when determining the power output of the turbine, maintaining fidelity with SolarReserve’s underlying engineering model, and (iv) demonstrating the ability of CSP to meet demand and/or market signals in a flexible and reliable manner by proactively controlling when stored energy is used.

The production scheduler algorithm identifies high-value time periods by examining the expected pricing schedule. Thermal energy is generated by the solar field as the solar resource is available, and the algorithm allows use of stored energy in time periods after it has been generated for power production. Stored energy must remain within lower and upper limits, and thermal energy collection must be curtailed once storage reaches the upper threshold. The optimal profile is a time-series power generation signal whose values fall within a continuous range of power production limits.

This approach succeeds in allocating generation to the highest-value time periods, but may be improved in several regards. Specifically, the energy allocation process does not auto-
matically value continuity in generation over time, resulting in an initial profile with frequent turbine starts and stops, which, if implemented in an operational facility, would increase the maintenance burden. In SolarReserve’s use of production scheduler, these alterations are handled via data post-processing and manual adjustments, which requires additional effort and limits the number of analyses that can be completed during the project development phase. Lastly, the problem is nonlinear because of operating mode integrality constraints and various functional relationships, and production scheduler lacks a mathematical model whose convexity is guaranteed; consequently, the identified solution carries a nontrivial risk of suboptimality.

By contrast, we pose our problem formally as a mixed-integer program (MIP) that can leverage state-of-the-art modeling languages and solvers [68, 69] to make the mathematical program whose instances contain thousands of variables and constraints tractable within a target evaluation time of several minutes. We maximize objective function value ($\mathcal{R}$), which is the summation of revenue and negative cost terms as described in the Appendix. Nonlinearity concerns are ameliorated by pre-processing certain subsystem models and by providing output performance data as parameters in the MIP formulation. Integrality characteristics are addressed using binary variables that reconstruct time-series and mode-of-operation behavior. Before the power cycle or receiver can produce electricity or thermal energy, respectively, start-up requirements must be satisfied, including both a minimum start-up period and a minimum energy state, both of which are surrogates for temperature considerations. In the latter case, the plant equipment cools during shutdown periods and must overcome the system’s thermal inertia to begin generating steam that powers the turbine. Likewise, the receiver consumes energy as it heats up and must complete a start-up procedure before producing useful thermal energy. Furthermore, turbine and heat exchanger equipment manufacturers limit the maximum rate of temperature increase during start-up to avoid thermal stress and mechanical failure risks. Both the energy and duration start-up requirements must be met before equipment can begin producing power. These requirements are implemented
as a constraint on the maximum energy delivered for start-up during any given time period. Although start-up must last for at least a minimum number of time steps, longer start-up durations are allowed in practice based on energy availability, and the model must provide this flexibility.

Two start-up scenarios are possible for the power cycle: (i) cold start-up, which occurs when the power cycle has shut down for any period of time and seeks to restart; and (ii) hot start-up, which occurs when the power cycle has been in standby mode and seeks to restart. Cold start-up requires an additional energy contribution and incurs more component wear and tear, whereas hot start-up can happen immediately (from the perspective of the hourly model).

Standby is a mode of operation in which a small (but non-trivial) amount of thermal energy is consumed during each time period to maintain the power cycle and/or receiver equipment in a hot state, ready to quickly ramp up for electricity generation; however, no electricity is produced in standby mode. Consequently, maintaining the power cycle in standby mode is of value if multiple start-up events are anticipated over a relatively short time span, or if the energy penalty or ramp rate requirement for start-up is sufficiently severe to justify the small rate of energy consumption by the power cycle.

The receiver can also operate in standby mode during cloudy periods to avoid the full start-up procedure, and, in doing so, consumes thermal energy from TES. The MIP accounts for receiver shutdown energy consumption in which the heliostat field provides sufficient energy to allow the salt to drain without freezing before the solar field ends operation for the day. The draining procedure requires approximately fifteen minutes while sunlight is available, and we model this effect as the consumption of 25% of the hourly energy used at the minimum receiver production rate.

4.5 Implementation

The typical model instance contains 912 variables and 1,615 constraints. AMPL and CPLEX presolve reductions result in a problem with an average of 442 variables and 652
constraints, and an average run time on a Dell PowerEdge R410 server running Ubuntu 14.04 with 12GB RAM, 16 Intel processors at 2.72GHz each of 0.43 seconds. By contrast, implementation of the model using LPSolve [70], which is a freeware MIP solver platform for C++, requires an average of 0.83 seconds per solve. Presolve reductions are less effective, producing instances with 890 variables and 920 constraints.

Figure 4.3 illustrates the dispatch optimization model within SAM whose interface provides both input and output display. The user modifies the inputs to emulate their technology configuration of interest, after which SAM models technical and financial performance using parameters specified in the interface to theit SAM Simulation Core. Therein lies the molten salt power tower technology model that contains a solar field design algorithm called SolarPILOT and detailed calculators for determining weather data and the performance of the collector, receiver, power block, and TES subsystems.

The Molten Salt Power Tower Model predicts annual electricity production by evaluating system performance over a sequence of hourly time steps, at each of which the CSP controller determines the best operational mode given the conditions endogenous and exogenous to the system. The CSP solver ensures that all of the interconnected inputs and outputs among the calculators agree with respect to the thermodynamic state of the system. In summary, the architecture in Figure 4.3 characterizes a molten salt power tower plant with storage, in which the hour-by-hour plant operation protocol is determined using a 48-hour time horizon that rolls forward in 24-hour increments.

The Production Forecast Model determines expected future thermal energy generation of the solar field. While it is possible to implement a variety of techniques for predicting electricity pricing, ambient temperature, and direct normal irradiance (DNI), this paper uses “perfect forecasting” in which the model generates expected performance by reading ahead in the weather file. SAM-MSPT incorporates time-series data from the weather and pricing databases corresponding to the horizon over which the model is solved.
The Engineering Performance Model (consisting of the CSP controller, CSP solver, and detailed performance calculators in Figure 4.3) predicts plant behavior and productivity over time using computationally expensive procedures derived from physically based, first-principles modeling of thermodynamics and heat transfer phenomena ([11], [12]). The MIP mathematical formulation, when solved with an appropriate algorithm, determines the time-series performance and operation of the plant using the forecast model and various operational constraints. In our results, we translate the objective function value of \( R \) into net revenue by taking fixed costs as sunk, maximizing revenue generated from electricity sales, and minimizing operational costs.

4.6 Results

This study compares the dispatch profile for the Rice project that is identified by the current approach with that of SolarReserve’s production scheduler algorithm. Design parameters for Rice are summarized in Table 4.1. The system consists of a power cycle capable of 163 MW<sub>e</sub> output with 8 hours of thermal storage, or 3,142 MW<sub>t</sub>-hr, and a receiver capable of 691 MW<sub>t</sub> production. Table 4.1 also defines the operational limits for the receiver.
Table 4.1: Case study plant design and control parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Units</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cycle design thermal input</td>
<td>MW_t</td>
<td>393</td>
</tr>
<tr>
<td>Cycle maximum gross output</td>
<td>MW_e</td>
<td>163</td>
</tr>
<tr>
<td>Cycle maximum net output</td>
<td>MW_e</td>
<td>150</td>
</tr>
<tr>
<td>Cycle minimum gross output</td>
<td>MW_e</td>
<td>37.5</td>
</tr>
<tr>
<td>Cycle start-up energy consumption</td>
<td>MW_t-hr</td>
<td>197</td>
</tr>
<tr>
<td>Cycle minimum start-up time</td>
<td>hr</td>
<td>0.5</td>
</tr>
<tr>
<td>Cycle standby consumption</td>
<td>MW_t</td>
<td>78.6</td>
</tr>
<tr>
<td>Receiver design thermal output</td>
<td>MW_t</td>
<td>691</td>
</tr>
<tr>
<td>Receiver maximum output</td>
<td>MW_t</td>
<td>691</td>
</tr>
<tr>
<td>Receiver minimum output</td>
<td>MW_t</td>
<td>173</td>
</tr>
<tr>
<td>Receiver start-up energy</td>
<td>MW_t-hr</td>
<td>173</td>
</tr>
<tr>
<td>Receiver minimum start-up time</td>
<td>hr</td>
<td>0.2</td>
</tr>
<tr>
<td>Thermal storage maximum charge</td>
<td>MW_t-hr</td>
<td>3,142</td>
</tr>
<tr>
<td>Levelized power cycle start-up cost</td>
<td>$/start</td>
<td>16,500</td>
</tr>
<tr>
<td>Levelized receiver start-up cost</td>
<td>$/start</td>
<td>950</td>
</tr>
<tr>
<td>Levelized ramping cost</td>
<td>$/ΔMW_e</td>
<td>10</td>
</tr>
</tbody>
</table>

and power cycle, and specifies assumed cost parameters for system start-up and production change (ramping) in the power cycle which are adapted from [90]. The solar field layout corresponding to this design is shown in Figure 4.4 and was generated using SolarPILOT; it is representative of the final design, but differs slightly from the layout determined by SolarReserve.

We select a pricing profile based on historical data for 2015 that was drawn from the CAISO Oasis database (oasis.caiso.com), and seek to demonstrate operations that maximize revenue generation in a volatile and diurnal environment. Figure 4.5 shows the relative pricing value at hourly intervals over the modeled year (top), and a selection of data from March overlaid with irradiance data (bottom). The relative pricing is calculated using the “locational marginal price” data, and dividing each value by the annual mean. A small set of hours each day accounts for a disproportionate share of revenue generation, and these peak hours do not coincide with solar resource availability, as illustrated in Figure 4.5. Irradiance data is taken from NREL’s national solar radiation database using the physical solar model.
[91], which provides historical records at the site of the plant. Note that the irradiance and pricing profiles are contemporaneous and co-located.

Results from the MIP embedded in SAM (hereafter referred to by shorthand as “SAM”) and production scheduler are shown in Table 4.2. Net electricity output measures the output that can be sold, and the reported values exclude negative production that results from plant parasitic consumption during hours in which the power cycle is not generating electricity. Production is also limited to 150 MW_e in both models. SAM generates approximately 0.5% more electricity over a typical year than production scheduler. A baseline PPA price of $96/MW_e-hr is assumed, which scales the market price multipliers to construct the (dimen-
sional) price schedule at which electricity can be sold over time. The resulting electricity sales are shown, with production scheduler exceeding SAM by 0.5%, though the shortfall is due to a trade-off in operations and maintenance costs, as reflected in SAM’s reduced expected costs. The number of turbine starts (per annum) shows a 67% reduction from production scheduler to SAM, and the average number of cycles per day is also substantially reduced by SAM, where one cycle corresponds with a full ramp from no generation to design-point generation (150 MW\textsubscript{e}) and back down to zero. The net revenue consists of nominal electricity sales minus start-up costs and ramping costs using the coefficients specified in Table 4.1, and SAM realizes a 15.3% improvement. Extended over the project lifetime of twenty-five years, the benefit of the current approach is over $200M, including revenue from sales and avoided maintenance costs.

Also shown in Table 4.2 is a comparison with the heuristic method used previously in SAM and briefly introduced in the *Current Dispatch Model* section. This algorithm does not account for pricing or weather forecasts, but rather dispatches based on a set of rules related to the current energetic state of the system. Both the current SAM optimization approach and the production scheduler algorithm greatly improve production and electricity sales in
comparison to the heuristic, but SAM more significantly improves net revenue.

Table 4.2: Metrics of interest and relative improvement of SAM over the original heuristic approach and production scheduler.

<table>
<thead>
<tr>
<th>Metric</th>
<th>SAM</th>
<th>Heuristic</th>
<th>PS</th>
<th>% Rel.</th>
<th>% Rel.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity sales ($)</td>
<td>69,581,282</td>
<td>-12.6</td>
<td>0.36</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Net electricity output (MW$_e$-hr)</td>
<td>631,749</td>
<td>-0.35</td>
<td>-0.54</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Turbine starts</td>
<td>254</td>
<td>49.2</td>
<td>204</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected maintenance cost ($)</td>
<td>4,188,621</td>
<td>49.2</td>
<td>204</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Turbine cycles per day</td>
<td>1.46</td>
<td>-20.3</td>
<td>46.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected maintenance cost ($)</td>
<td>796,797</td>
<td>-20.3</td>
<td>46.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annualized maintenance costs ($)</td>
<td>4,985,418</td>
<td>38.1</td>
<td>179</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Net revenue ($)</td>
<td>64,595,863</td>
<td>-16.5</td>
<td>-13.4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The advantage of accounting for operational costs as part of the dispatch optimization is apparent with respect to expected net revenue, and the operational advantage is furthermore illustrated in Figure 4.6. Both SAM and production scheduler electricity production is shown over a span of six days in May, along with the concomitant pricing schedule. SAM and production scheduler largely match in the timing and magnitude of production, but SAM anticipates upcoming periods of high production and maintains turbine operation at the minimum output threshold rather than requiring a shut-down and start-up event. Over the period shown, SAM requires two turbine starts while production scheduler requires fifteen. The financial impact of improved operations will be realized over longer periods of time in the form of reduced maintenance frequency and longer component lifetime.

The revenue attained during each day (left), each week (center), and each month (right) is shown in Figure 4.7 for production scheduler (horizontal axis) and SAM (vertical axis). Revenue exclusively from sales is shown on top, and net revenue (electricity sales minus start-up and ramping costs) is shown on the bottom. For periods in which both models achieve the same accumulated revenue, the plotted points fall along the line of perfect agreement. These plots show that the daily revenue from each approach can vary due to differences in
the timing of turbine starts, as the current approach emphasizes operational continuity more than the production scheduler algorithm does. With respect to electricity sales, increasing time horizon length causes short-term differences to average out, yielding increasingly correlated revenue projections. However, the SAM approach improves net revenue by accounting for operational costs. This result indicates that the revenue from electricity sales is fairly insensitive to the decision variable values near the optimum, but small sacrifices in electricity sales may increase net revenue by reducing component wear and tear costs while also easing the challenge to plant operators of executing a highly variable generation profile.

Power generators may also obtain significant revenue via “capacity payments,” in which a marketplace further incentivizes reliable production during the highest-value time periods by making a post hoc payment based on the fraction of power delivered divided by the theoretical plant capacity for production during those time periods [92]. For example, a capacity payment might be issued at a rate of $200 per MW capacity per year for the fraction of power generated during the top 100 most highly-priced hours. From this perspective, we consider the ability of SAM, production scheduler, and the heuristic algorithm to gain
Figure 4.7: Comparison of expected revenue using the production scheduler algorithm (horizontal axis) and SAM (vertical axis) as aggregated over three time horizons – daily, weekly, and monthly. Revenue from sales is shown on the top, and net revenue including costs is shown on the bottom. The line of perfect agreement is shown in each case. Note that the left and center plot axes are logarithmic.

revenue from capacity payments. Figure 4.8 shows the fraction of the capacity payment that is gained by each algorithm as a function of the number of top-priced hours of the year that are subject to a capacity incentive. Returning to the aforementioned example, if a capacity payment is issued for the most highly-priced 100 hours of the year, both SAM and production scheduler would receive approximately 98% of the capacity payment, while the heuristic method would only gain 78%, in theory costing the operator millions of dollars in revenue per year. This result illustrates both the value of CSP as a reliable generator and the importance of optimizing dispatch for the market in which the plant will operate.
4.7 Impacts and Future Work

We present a novel approach for identifying and evaluating the optimal energy production schedule for both thermal and electrical power subsystems in a CSP molten salt power tower plant, and consider its behavior in comparison with an alternate approach developed by SolarReserve. The tool is used during a multi-year project development period to identify improved plant designs and facilitate contractual agreements between the technology provider and other stakeholders, including financial and investment firms, governmental agencies, and engineering, procurement, and construction firms. The production scheduler approach used by SolarReserve succeeds in identifying high-revenue operational schemes, while our method similarly maximizes sales revenue while addressing implementability and long-term maintenance requirements.

In follow-on work, we plan to use stochastic programming to account for uncertainty in weather and pricing forecasts when determining the optimal operations schedule such that
forecasting errors minimally affect a plant’s ability to generate revenue. Work presented here is part of a larger effort regarding plant design, operations, and maintenance modeling and optimization. Because design decisions impact operations and maintenance requirements – and *vice versa*, a holistic design approach must account for all of these aspects. The broader study seeks to develop methodology and tools whereby plant design, and operations and maintenance policies are co-optimized, streamlining existing technology and providing a systematic approach for introducing new components or subsystems into the technology framework.

4.8 Appendix - Formulation

We refer to our dispatch model as \((\mathcal{R})\); this model is adapted from [93]. Units, where appropriate, are provided next to the corresponding parameter or variable. (Initialization parameters used to set variable values at \(t = 0\) follow variable notation and are not included here.)

Indices and Sets

- \(t \in \mathcal{T}\): all time steps in the time horizon, \(\mathcal{T} = |\mathcal{T}|\)

Parameters

- \(Q_{t}^{in}\): energy generated by the solar field in time \(t\) [kW\(_t\)]
- \(P_t\): electricity sales price [\(\text{¢}/\text{kWe}\text{-hr}\)]
- \(\dot{W}_t^{net}\): net power production upper limit, \(t \in \mathcal{T}\) [kWe]
- \(\dot{W}_t^{min}\): minimum net power production, \(t \in \mathcal{T}\) [kWe]
- \(\eta_t\): normalized condenser parasitic loss, \(t \in \mathcal{T}\) [-]
- \(\gamma_t\): exponential time weighting factor; \(\Gamma^{(t)}\), where \(\Gamma \approx 0.99\)
- \(\Delta_t^{rs}\): estimated fraction of time step \(t\) used for receiver start-up [-]
• $\bar{P}$: mean sales price ($\$/kW$_{\text{e}}$-hr); $\sum_{t \in T} P_t / T$

• $\eta_{\text{tamb}}$: cycle efficiency adjustment factor

• $\eta_{\text{des}}$: cycle nominal efficiency

• $\eta_p$: slope of linear approximation of power cycle performance curve

• $\tau$: frequency of optimization problem execution [hr]

• $E^u$: energy storage capacity [kW$_t$-hr]

• $E^r$: required energy consumed to start receiver [kW$_t$-hr]

• $E^c$: required energy consumed to start cycle [kW$_t$-hr]

• $E^{hs}$: heliostat field startup or shutdown parasitic loss [kWe-hr]

• $Q^u$: cycle thermal power capacity [kW$_t$]

• $Q^l$: minimum operational thermal power input to cycle [kW$_t$]

• $W^u$: cycle electric power rated capacity [kW$_e$]

• $W^l$: minimum electric power output from cycle [kW$_e$]

• $\dot{W}^h$: heliostat field tracking parasitic loss [kWe]

• $\dot{W}^b$: power cycle standby operation parasitic load [kWe]

• $\dot{W}^{rsb}$: Tower piping heat trace parasitic loss [kWe-hr]

• $Q^{ru}$: allowable power per period for receiver start-up [kW$_t$]

• $Q^{rl}$: minimum operational thermal power delivered by receiver [kW$_t$]

• $Q^{rsd}$: required thermal power for receiver shut-down [kW$_t$]

• $Q^{rsb}$: required thermal power for receiver standby [kW$_t$]
- \( Q^c \): allowable power per period for cycle start-up \([\text{kW}_t] \)
- \( Q^b \): standby thermal power consumption per period \([\text{kW}_t] \)
- \( L^r \): receiver pumping power per unit power produced \([\text{kW}_e/\text{kW}_t] \)
- \( L^c \): cycle HTF pumping power per unit energy consumed \([\text{kW}_e/\text{kW}_t] \)
- \( C^{rsu} \): penalty for receiver start-up (from 0) \([\$] \)
- \( C^{rhs} \): penalty for receiver start-up (from hot standby) \([\$] \)
- \( C^{csu} \): penalty for cycle start-up (from 0) \([\$] \)
- \( C^{chs} \): penalty for cycle start-up (from hot idle) \([\$] \)
- \( C^{\delta W} \): penalty for any positive change in electricity production \([\$/\text{kW}_e] \)
- \( \Delta \): time step duration \([\text{hr}] \)
- \( \Delta^l \): minimum duration of receiver start-up in period \([\text{hr}] \)
- \( M \): a sufficiently large number \([\text{}] \)

**Continuous Variables**

- \( x_t \): cycle thermal power consumption at \( t \) \([\text{kW}_t] \)
- \( \dot{w}_t \): electrical power generation at \( t \) \([\text{kW}_e] \)
- \( \dot{w}^\delta_t \): positive change in electricity production at \( t \) \([\text{kW}_e] \)
- \( x^r_t \): thermal power delivered by the receiver at \( t \) \([\text{kW}_t] \)
- \( x^{rsu}_t \): receiver start-up power consumption at \( t \) \([\text{kW}_t] \)
- \( u^{rsu}_t \): receiver start-up energy inventory at \( t \) \([\text{kW}_t\cdot\text{hr}] \)
• $u_t^{csu}$: cycle start-up energy inventory at $t$ [kW$_t$-hr]

• $s_t$: TES reserve quantity at $t$ (auxiliary variable) [kW$_t$-hr]

**Binary Variables**

• $y_t^r$: 1 if receiver is generating “usable” thermal power at time $t$; 0 otherwise

• $y_t^{r_{su}}$: 1 if receiver is starting up at time $t$; 0 otherwise

• $y_t^{r_{sb}}$: 1 if receiver is in standby mode at time $t$; 0 otherwise

• $y_t^{r_{sd}}$: 1 if receiver shut down at time $t$; 0 otherwise

• $y_t^{csu}$: 1 if cycle is starting up at time $t$; 0 otherwise

• $y_t^{csb}$: 1 if cycle is in standby mode at time $t$; 0 otherwise

• $y_t^{csd}$: 1 if cycle is shutting down at time $t$; 0 otherwise

• $y_t$: 1 if cycle is generating electric power at time $t$; 0 otherwise

• $y_t^{r_{sup}}$: 1 if receiver is starting up at time $t$ and was not in standby mode at time $t-1$; 0 otherwise

• $y_t^{r_{hsp}}$: 1 if receiver is starting up at time $t$ and was in standby mode at time $t-1$; 0 otherwise

• $y_t^{c_{sup}}$: 1 if cycle is starting up at time $t$ and was not in standby mode at time $t-1$; 0 otherwise

• $y_t^{c_{hsp}}$: 1 if cycle is starting up at time $t$ and was in standby mode at time $t-1$; 0 otherwise

The objective function and constraints follow:
(R) maximize \[ \sum_{t \in T} \left[ \Delta \cdot P_t \left( \gamma_t \eta_t \hat{w}_t - L^r (x_t^r + x_t^{rsu} + Q_t^{rsb}) - L^c x_t \right) \right. \\
- \hat{W}^h y_t^r - \hat{W}^b y_t^{csb} - E^{hs} / \Delta \cdot y_t^{rsb} - E^{hs} / \Delta \cdot y_t^{rsd} \left. \right] \\
- \gamma_t (C^{rsu} y_t^{rsu} + C^{rhsp} y_t^{rhsp} + (E^{hs} + \Delta \hat{W}^{rsb}) y_t^{rsu}) \\
- \gamma_t (C^{csu} y_t^{csu} + C^{chsp} y_t^{chsp} + y_t^{csd} + C^{sw} \hat{w}_t^\delta) \\
+ \gamma_t (\bar{P} x_t^r + y_t^r) \] (4.1)

subject to

(Receiver Start-up)

\[ u_t^{rsu} \leq u_{t-1}^{rsu} + \Delta \cdot x_t^{rsu} \quad \forall t \in T : t \geq 2 \] (4.2a)

\[ u_t^{rsu} \leq E^r y_t^{rsu} \quad \forall t \in T \] (4.2b)

\[ y_t^r \leq \frac{u_t^{rsu}}{E^r} + y_{t-1}^r \quad \forall t \in T : t \geq 2 \] (4.2c)

\[ y_t^{rsu} + y_t^r \leq 1 \quad \forall t \in T : t \geq 2 \] (4.2d)

\[ x_t^{rsu} \leq Q^{rsu} y_t^{rsu} \quad \forall t \in T \] (4.2e)

if \( Q_t^{in} = 0 \) then:

\[ y_t^{rsu} = 0 \quad \forall t \in T \] (4.2f)

(Receiver Supply and Demand)

\[ x_t^r + x_t^{rsu} + Q_t^{rsd} y_t^{rsd} \leq Q_t^{in} \quad \forall t \in T \] (4.3a)

\[ x_t^r \leq Q_t^{in} y_t^r \quad \forall t \in T \] (4.3b)

\[ x_t^r \geq Q_t^{in} y_t^r \quad \forall t \in T \] (4.3c)

if \( Q_t^{in} = 0 \) then:

\[ y_t^r = 0 \quad \forall t \in T \] (4.3d)

(Logic Governing Receiver Modes)

\[ y_t^{rsu} + y_t^{rsb} \leq 1 \quad \forall t \in T \] (4.4a)

\[ y_t^r + y_t^{rsb} \leq 1 \quad \forall t \in T \] (4.4b)

\[ y_t^{rsb} \leq y_{t-1}^r + y_{t-1}^{rsb} \quad \forall t \in T : t \geq 2 \] (4.4c)

\[ y_t^{rsup} \geq y_t^{rsu} - y_{t-1}^{rsu} \quad \forall t \in T : t \geq 2 \] (4.4d)

\[ y_t^{rhsp} \geq y_t^r - (1 - y_{t-1}^{rsb}) \quad \forall t \in T : t \geq 2 \] (4.4e)

\[ y_{t-1}^{rsd} \geq (y_{t-1}^r - y_{t-1}^r) + (y_{t-1}^{rsb} - y_{t-1}^{rsb}) \quad \forall t \in T : t \geq 2 \] (4.4f)
(Cycle Start-up)
\[
y_t \leq \frac{u_{csu}^{csu}}{E_c} + y_{t-1} + y_{csb}^{csb} \quad \forall t \in T : t \geq 2 \tag{4.5a}
\]
\[
x_t + Q^c y_{csu}^{csu} \leq Q^u y_t \quad \forall t \in T \tag{4.5b}
\]
\[
x_t \leq Q^u y_t \quad \forall t \in T \tag{4.5c}
\]
\[
x_t \geq Q^l y_t \quad \forall t \in T \tag{4.5d}
\]

(Power Supply and Demand)
\[
\dot{w}_t \leq \frac{\eta^\text{amb}_{t}}{\eta^\text{des}_{t}} (\eta^p x_t + y_t(W^u - \eta^p Q^u)) \quad \forall t \in T \tag{4.6a}
\]
\[
\dot{w}_t^s \geq \dot{w}_t - \dot{w}_{t-1} \quad \forall t \in T : t \geq 2 \tag{4.6b}
\]
If \( \dot{W}_t^\text{net} \geq \dot{W}_t^\text{min} \) then:
\[
\dot{W}_t^\text{net} \geq \dot{w}_t (1 - \eta^c_t) - L^r (x_t^r + x_{rsu}^r) - x_t L^c - y_{t} y_{csu} \left( \frac{\dot{W}_{rsu}^r}{\Delta} + \frac{E_{hs}}{\Delta} \right) - \dot{W}^h y_t^r - y_{csb}^c \dot{W}^h \forall t \in T \tag{4.6c}
\]
else:
\[
\dot{w}_t = 0 \quad \forall t \in T \tag{4.6d}
\]

(Logic Governing Cycle Modes)
\[
y_{csu}^t + y_{t-1} \leq 1 \quad \forall t \in T : t \geq 2 \tag{4.7a}
\]
\[
y_{csb}^t \leq y_{t-1} + y_{csb}^{csb} \quad \forall t \in T : t \geq 2 \tag{4.7b}
\]
\[
y_{csu}^t + y_{csb}^{csb} \leq 1 \quad \forall t \in T \tag{4.7c}
\]
\[
y_t + y_{csb}^{csb} \leq 1 \quad \forall t \in T \tag{4.7d}
\]
\[
y_{csup}^t \geq y_{csu}^t - y_{csu}^{csu} \quad \forall t \in T : t \geq 2 \tag{4.7e}
\]
\[
y_{chsp}^t \geq y_t - (1 - y_{csb}^{csb}) \quad \forall t \in T : t \geq 2 \tag{4.7f}
\]
\[
y_{csd}^t \geq (y_{t-1} - y_t) + (y_{csb}^{csb} - y_{t}^{csb}) \quad \forall t \in T : t \geq 2 \tag{4.7g}
\]
\[
y_{csu}^t \leq u_{csu}^{csu} + \Delta \cdot Q^c y_{csu}^t \quad \forall t \in T : t \geq 2 \tag{4.7h}
\]
\[
y_{csu}^t \leq M y_{csu}^t \quad \forall t \in T \tag{4.7i}
\]

(Energy Balance)
\[
s_t - s_{t-1} = \Delta \cdot [x_t^r - (Q_c y_{csu}^t + Q_b y_{csb}^{csb} + x_t + Q_{rsb} y_{rsu}^{rsb})] \quad \forall t \geq 2 \tag{4.8a}
\]
\[
x_{t+1} + Q_b y_{t+1}^{csb} \leq \frac{s_t}{\Delta_{t+1}^{rsb}} - \Delta \cdot (-3 + y_{t+1}^{csu} + y_t + y_{t+1} + y_{csb}^{csb} + y_{t+1}^{csb}) \quad \forall t \in T : t \leq T - 1 \tag{4.8b}
\]
The objective maximizes electricity sales, which are represented as the summation over time of the product of electricity price and power generation less parasitic losses. Cost penalties associated with start-up, shut-down, and change in electricity production between time steps are subtracted from the revenue. Several terms in the objective function are weighted by an exponentially decaying multiplier to prioritize energy production earlier in the time horizon. The final term in the objective function incentivizes energy dumping from the solar field – if necessary – to occur later in the time horizon to improve agreement between the expected net electricity production and the actual modeled value, as pumping parasitics associated with solar field operation are significant.

We consider receiver start-up inventory and the criteria that must be satisfied in order for it to produce useful power. Constraint (4.2a) tracks start-up energy “inventory” using an inequality, rather than an equality, to allow inventory to reset to zero in time periods following start-up completion; inventory is naturally maximized by the problem and can only be nonzero for time steps in which the receiver is starting up by Constraint (4.2b).

Constraint (4.2c) allows receiver power production only after start-up has been completed or when the receiver was operating in the previous time step. Constraint (4.2d) ensures that receiver start-up mode does not persist while the receiver is operating in power-producing mode by disallowing start-up in the time step following normal power production operation. Constraint (4.2e) ensures that the actual power used for receiver start-up is no more than the ramp rate limit for each time step. Constraint (4.2f) prevents receiver start-up from occurring in time periods with trivial solar resource.
The total power produced by the receiver has an upper bound of the available energy $Q_t^m$, and any start-up or shutdown energy consumption detracts from production according to Constraint (4.3a). The receiver can only generate thermal power when it is in power-producing mode (i.e., $y_t = 1$) by Constraint (4.3b). Constraint (4.3c) is enforced because of molten-salt pump operating limits and heat transfer requirements in the receiver, ensuring that the receiver energy generation must satisfy a minimum threshold. Constraint (4.3d) ensures that the receiver power-producing mode does not persist when no energy is available.

While the receiver is in standby mode, molten salt is circulated between the cold TES tank and receiver, enabling fast restart. A smaller hot start-up penalty is enforced when beginning normal operation from standby mode. Neither standby and start-up modes (Constraint (4.4a)) nor standby and power-producing modes (Constraint (4.4b)) can coincide. Standby mode can persist over time, but must follow time steps in which the receiver was either in standby or power-producing mode (Constraint (4.4c)). Constraints (4.4d) and (4.4e) enforce logic associated with incurring a penalty for receiver start-up from an off or standby state, respectively. Constraint (4.4f) enforces the logic for shut-down from a power producing or standby state.

Constraint (4.5a) allows normal cycle operation only when start-up has been completed, when the cycle was previously operating, or when the cycle has been in standby mode. Constraint (4.5b) limits the cycle start-up rate, and Constraint (4.5c) enforces a maximum thermal power consumption limit by the power cycle. When operating, the cycle must produce a minimum amount of power enforced by Constraint (4.5d). Constraint (4.6a) determines electrical power production based on a linear cycle performance curve and the ambient temperature efficiency. An optimized dispatch profile may result in electricity production lower than the CSP plant design-point during certain time periods in order to conserve stored thermal energy for more favorable future market conditions, or to avoid penalties associated with shut-down and start-up, for example. However, power cycle efficiency is adversely affected by departure from design [11]. The relationship between thermodynamic efficiency
and thermal input is nonlinear and, consequently, poses computational challenges. In order to improve tractability in the corresponding optimization model, we resolve the nonlinearity $\eta^{\text{cycle}}(x_t) \cdot x_t$ by modeling electrical output as an approximately linear function of cycle thermal power consumption, shown in Constraint (4.6a). The linear coefficient is the quotient of the difference between the minimum and maximum output from the power cycle and the corresponding expression for the thermal power input.

$$\eta^p = \frac{W^u - W^l}{Q^u - Q^l} \tag{4.10}$$

The positive change in electrical power production is determined by Constraint (4.6b). The presence of $\dot{w}_t^p$ in the objective function provides a disincentive to vary power production from one time step to the next, thereby reducing system cycling and more closely representing operator-preferred generation profiles. The appropriate magnitude of this penalty parameter is unknown but is explored further in a sensitivity analysis provided in Section 4. Start-up mode persistence is prevented in Constraint (4.7a). Standby mode can persist according to the analogous receiver requirements (Constraint (4.7b)). Standby and start-up modes cannot coincide (Constraint (4.7c)), nor can standby and power-producing mode (Constraint (4.7d)). Constraint (4.7e) enforces the penalty logic for start-up from an off state while (4.7f) enforces the penalty logic for start-up from a standby state. Constraint (4.7g) enforces the logic for shut-down from a power-producing or standby state. Power cycle operation constraints largely mirror those of receiver operations and include: Constraint (4.7h) tracks start-up energy inventory, and Constraint (4.7i) allows nonzero inventory only during periods of cycle start-up.

The energetic state of the system implicates positive and negative power terms, and the charge state of thermal storage ($s_t$) accounts for the cumulative difference between them. Several additional constraints regarding TES state of charge are enforced as follows: Constraint (4.8a) ensures that energy into and out of TES balance with the charge state, and the conversion from power to energy introduces a time step parameter $\Delta$. Constraint (4.8b) ad-
addresses an artifact arising from the difference between the modeling time resolution (hourly) and the amount of time required to start the plant, which may not be in units of whole hours. If the power cycle is either running or in standby in time step $t$ and in time step $t+1$, and if the receiver starts up in time $t+1$, then the minimum charge level in TES in time $t+1$ must be sufficient to carry operation through the receiver start-up period $\Delta_{rs}^t$. Note that $y_t + y_{cs}^{cab} \leq 1$ is enforced elsewhere. Equation (4.11) determines the expected fraction of each time step that would be used for receiver start-up, if applicable.

$$\Delta_{rs}^t = \min \left\{ 1, \max \left\{ \frac{\Delta_t^1}{\max \{\epsilon, Q_{in}^{m,1}\}}, \frac{E_c}{\Delta_t^1} \right\} \right\}$$

(4.11)

Constraints (4.8a)-(4.8b) only track TES state of charge based on energy flow bookkeeping, not temperature. Accounting for energy quality in the TES system via temperature of the molten salt introduces non-linear complexity and is not necessary in this formulation as previously discussed. Constraint (4.9a) ensures non-negativity for receiver start-up power consumption and receiver start-up energy inventory. Non-negativity for $x_r^t$ is ensured via Constraint (4.3c). Constraint (4.9b) ensures non-negativity for cycle start-up energy inventory, electrical power generation, and positive change in electricity production, and it constrains the upper bound of stored energy. Non-negativity for $x_t$ is ensured via Constraint (4.5d). Constraints (4.9c) and (4.9d) enforce binary requirements.

### 4.9 Acknowledgements

This work was funded by the United States Department of Energy – Energy Efficiency and Renewable Energy under award numbers DE-EE00025831 and DE-EE00030338. The authors gratefully acknowledge Charles Diep and Adam Green at SolarReserve\textsuperscript{TM} for feedback on modeling priorities and plant operations, Will Hamilton and Jennifer DiCarlo at Colorado School of Mines for her contributions to the MIP mathematical formulation, Janna Martinek at the National Renewable Energy Laboratory for contributions and testing of the LP Solve implementation and net power constraint, Mark Mehos at the National Renewable Energy Laboratory for guidance on market factors, and Steven Janzou at the National Renewable
Energy Laboratory for help with implementation of hourly market factors.
CHAPTER 5
SUMMARY AND CONCLUSIONS

This research consists of three specific objectives that relate to methods for reducing computational expense in the solar field layout and characterization process, formulation of a dispatch optimization model for CSP, and application of the research in collaboration with industry to a project under development. Of primary importance are the advances in computation and optimization for CSP applications, but a secondarily important aspect of this research is the extension of existing modeling platforms such as SAM and SolarPILOT which maximize the impact of the research outcomes. Each project objective is reviewed as follows, along with publication considerations, and the chapter concludes with recommendations for future work.

5.1 Optical Modeling Methodology Development

The first research objective seeks to identify and instantiate methods for reducing the computational expense of designing and characterizing the solar field. After defining high-level system sizing and component geometry parameters, this is the first step in predicting techno-economic performance for a particular technology instance. Previous work has produced software that is capable of simulating CSP systems with a large degree of flexibility and robustness but which lack expeditious initial design and characterization capabilities. Work described in Chapters 2 and 3 describe in detail the efforts undertaken to address these shortcomings.

Specific accomplishments include: (i) adoption and expansion of the Hermite series model for flux density applied to individual heliostats, offering flexibility in the heliostat field layouts that can be modeled and in the choice of heliostat-aiming algorithms, while executing calculations orders of magnitude more quickly than the more common Monte-Carlo ray tracing techniques, (ii) development of heliostat grouping techniques that limit the number of
potential heliostat interactions that must be considered, reducing a problem of exponential complexity to one which solves in linear time, (iii) application of geometric heliostat blocking and shading calculations that do not require expensive ray tracing calculations, (iv) prediction of annual heliostat power delivery using novel performance weighting techniques, (v) development of an exact solution for mathematical scaling of the flux distribution to ensure accurate numerical integration when small heliostats are used, and (vi) integration of the SolTrace ray tracing engine alongside the analytical model to provide verification of optical performance results.

SolarPILOT serves as an implementation platform for advances made as part of the thesis research. Project development – including dispatch optimization – is only meaningful if the energy input profile to the system from the solar field is realistic. Work toward this objective has been realized through the SolarPILOT development effort.

5.2 Dispatch Optimization

Chapter 3 describes a dispatch optimization strategy for CSP with TES, the purpose of which is to maximize the revenue stream and minimize operational costs derived from subsystem starts and stops. Given the inadequacies of heuristic plant control and the lack of dispatch optimization methods that fully account for the complexities of CSP plant operation, the described functionality represents a significant improvement towards understanding the impact of operational decisions on project techno-economic performance.

We formulate and describe an extensive MIP model that replicates complex and interconnected processes in a CSP plant with sufficient accuracy and greatly improved tractability over alternative, purely non-linear or heuristic approaches. Processes such as receiver start-up, standby, power cycle start-up, stand-by, and off-design operation are accounted for with constraints involving integer variables, while other processes are approximated with linear expressions. The objective function measures revenue generation via electricity sales while penalizing start-up costs, production ramping costs, and parasitic loads, and allowing the user to weight variables as a function of time. The formulation emphasizes fidelity with the
SAM engineering performance models, because the optimized dispatch profile is used within the SAM simulation to set operational targets, and mismatches between the simplified MIP and SAM’s performance models can result in sub-optimal operation. Constraints impose operational limits, ensure necessary sequences (e.g., satisfaction of start-up requirements) are followed, and accommodate real-world contractual requirements – as in the case of the net power constraint which is discussed in some detail.

The dispatch optimization model, once formulated, is exercised to demonstrate the value of the approach relative to previously-used heuristic methods. The analysis considers a “typical” molten salt plant with TES under four market scenarios, and explores how optimized dispatch affects the optimal sizing of the TES and solar field subsystems via an enumerative survey of the design space; significant differences in sizing and realized PPA price result. Cost penalties for start-up and ramping processes factor into the optimal dispatch profile, and Chapter 3 presents the sensitivity of the following metrics to both cycle start-up and power output ramping cost penalties, namely: the number of turbine starts incurred annually, the number of operational cycles per day – on average, annual energy production, and PPA price. We observe substantial qualitative and quantitative alterations in production with changes to these penalty values, as exemplified by the 60% reduction in turbine starts at elevated start-up cost penalties while PPA price and annual energy remain essentially constant. These results imply that substantial savings may be realized through operational changes that reduce component wear and tear without compromising revenue from electricity sales.

A publication describing this work was submitted to the journal Applied Energy which emphasizes – among other topics – issues related to energy conversion modeling and forecasting. The readership community for Applied Energy is relatively broad and may overlap in dispatch optimization interests for non-CSP technologies.
5.3 Application

The final thesis objective is to generate new insight into dispatch optimization for CSP by exercising the modeling tools and methods developed in Chapters 2 and 3. We do so by undertaking a collaborative analysis with SolarReserve who have made use of both the solar field layout and characterization tools in SolarPILOT and the dispatch optimization techniques, and applied them to CSP plants currently under development. This adoption has provided several benefits. These include (i) the amount of time needed to evaluate a particular plant configuration under consideration is significantly shorter, improving the end product that they offer by allowing more extensive project evaluation; (ii) the confidence in the ability of a plant to increase revenue by following an optimized dispatch profile has increased, owing to the more operator- and equipment-friendly profiles generated by our approach; and (iii) the transparency of implementing our methods in software that is publicly available and independently developed enhances the credibility – and, ultimately, the ability to obtain investment and financing – of their technology.

Chapter 4 describes the process of modeling SolarReserve’s technology using our tools, and compares the optimized dispatch profiles relative to their production scheduler tool. The results are favorable, lending credence to SolarReserve’s privately-developed approach while improving operational amenability and increasing lifetime net revenue. Joint work with SolarReserve has likewise benefited our research by identifying practical operations requirements (such as the net power constraint) that affect the mathematical approach and final results but are not self-evident from an academic standpoint. The study also demonstrates that the objective function is relatively insensitive to a subset of variable values near the optimal solution; in practical terms, this signifies that practical operation considerations such as production ramping rates can be accommodated in many cases with a trivially adverse impact on the achieved objective function value.

A journal publication describing this work is currently being drafted and will be submitted to the journal Interfaces which focuses on the practice and applications of operations
research (including dispatch optimization) in commerce, industry, government, or education. It encourages submissions in which operations research and applied mathematics research is used to improve operations, reduce costs, or improve the competitive position for enterprises.

5.4 Future and Recommended Work

The accomplishments presented in this thesis provide a framework for future research and analysis, and this section describes several such topics of interest.

5.4.1 Dispatch subject to uncertainty

CSP systems are often designed to allow for TES charging by generating more thermal power than can be instantaneously consumed by the power cycle. If a conservative production schedule is implemented in which stored energy is preferentially reserved exclusively for high-value hours, a plant may lose revenue by reaching the state of maximum charge and being forced to curtail thermal energy collection. Alternatively, if an aggressive electricity production schedule is implemented, the plant may not retain sufficient TES state of charge to generate electricity when revenues would be highest. The accuracy of solar resource and pricing forecasts thereby influence whether a production schedule can realize maximum revenue.

Both price and solar resource forecasts are inherently uncertain because of the chaotic nature of local weather patterns, and the magnitude of uncertainty generally increases with the forecast horizon. A potentially productive research question is thus: how should CSP plants operate to maximize revenue given uncertainty in forecasts, variable energy collection over time, and physical system operational limitations?

An answer to this question portends a significant outcome. As the global community struggles to address the reality of climate change, growth in renewable energy technology deployment offers a mitigating path. However, resource variability must be countered with reliable and dispatchable renewable technologies. Reliability is achieved at a cost, and that cost has yet to be accurately quantified for CSP because previous analyses have not sought
an optimized dispatch strategy that directly accounts for the reality of forecast uncertainty. This research would provide an important contribution toward quantifying the impact of replacing fossil fuel generators with renewable energy technologies.

Answering this question requires a cadre of technology simulation and characterization tools that include thermodynamic, heat transfer, and optical models, a mixed integer linear program formulation and solver, forecast uncertainty models, methods for stochastic optimization, and financial modeling tools. The work presented here has advanced research capabilities substantially, but optimization methods and analyses that account for forecast uncertainty remain outstanding.

5.4.2 System optimization

The thesis research is part of a broader project at NREL on CSP system design and O&M optimization. NREL is partnering with Colorado School of Mines, Northwestern University, Argonne National Laboratory, and SolarReserve to develop a tool and methodology for plant design and operation optimization. Several key outcomes are targeted by the NREL project. The first goal is to establish existing O&M costs following the template provided by previous costing studies (e.g., Turchi and Heath (2013) [94]). The next is to elucidate the ordinarily overlooked trilateral relationship between design-point criteria, initial component cost, and lifetime O&M costs. A rigorous modeling and solution approach emphasizes a clear and repeatable methodology, providing insight into the nature of the relationships while leaving the detailed engineering and costing exercises to the technology developers who are best suited for that work. Ultimately, this work plans to deliver a tool and methodology for use by entities that have access to their own proprietary design and cost information. The thesis research contributes to the evaluation of the system-wide optimization model by ensuring that the dispatch schedule within the simulation is optimal, maximizing revenue subject to forecast uncertainty over each daily dispatch optimization window. In essence, the thesis research provides a “realistically optimal” revenue evaluation to be used by the broader NREL project.
5.4.3 Application to other technologies

This research considers CSP power tower systems with molten salt TES, which is one specific manifestation of CSP with TES, albeit the most commercially promising one at the time of this writing. In principle, the dispatch optimization methodology described in Chapters 3 and 4 may be applied to any system comprised of energy collection, storage, and production units, and is especially relevant to technologies in which operation is modal or discontinuous, requires start-up procedures, and operates over forecast time horizons of one to three days. Examples include PV with battery storage, nuclear power plants with molten salt storage, and other CSP technologies capable of large-scale energy storage such as parabolic troughs and linear Fresnel. Extension of the current work to these areas would require modification to both the MIP formulation and any simulation models in which the dispatch optimization model is embedded. In particular, simulation control schemes used to determine the timing and magnitude of power production must be modified to accept a schedule generated by the MIP solution, and algorithms for performance forecasting and calculating approximate (linearized) performance coefficients must be defined.
REFERENCES CITED


