ECE 105 Final Project
Concluding Report

Matt Barnard

Fall 2019

Abstract

Solar energy collection is a paramount technology for meeting the growing energy needs of modern societies. Solar power is optimal from first principles: all other forms of power generation are derived from solar energy, through geologic, climatological, or biologic conversions–each of which may span enormous time periods and many steps of non-ideal efficiency. Despite this theoretical optimality, solar power has largely failed to upset the global market for non-solar sources. High-pollutant processes such as fossil fuel burning and nuclear fission continue to enjoy near-endless demand and continuing development. Further, the process of fracking has increased the environmental impact of fossil fuel consumption, causing demonstrable harm to the ways of life of peoples in the fracked region; in addition to causing geologic disturbances the consequences of which have yet to be illuminated.

We suggest that a major impediment to the dominance of emerging solar power technologies is two mutually compounding factors: the technologies have failed to meet performance expectations despite their theoretic potential; and as such the optimism and drive of investors, governmental powers, and demanding consumers have consequently waned.

We have therefore developed a model for predicting the future payoffs of investment in solar power infrastructure given realistic expectations of technological advancement. We claim that the details of technological development are largely opaque to most people, with even summaries of growth buried in academic articles. Our model synthesizes these summaries into a format consumable in any presentation, report, or pamphlet, and in a way that maintains accuracy while also maximizing on agreeable interpretations by consumers. In this paper we lay out the development of that model.

Background

A major difficulty in establishing photovoltaics as a competitive energy industry is overcoming shortsightedness in sociopolitical intuitions. Investment in production and installation is often measured against current or past performance, rather than accurate predictions of future performance. Public opinion plays a large role in establishing the consumer demand that might drive changes in industry focus. The public is generally altogether unaware of the state of research as it relates to future predictions, instead engaging with only current breakthroughs highlighted by popular media outlets.

To be convinced of the potentially high investment quality of the solar industry, individual investors as well as public consumers must have a tangible mental model of accurately predicted benefits.

Proposal

We sought to develop an interactive model for judging the investment quality of solar infrastructure, accounting for technological improvements that boost performance of that infrastructure. Our model would consider the following parameters:

1. Realistic expectations for immediate returns on infrastructure investment, in terms of usable power generation capacity, and
2. the impact of current technological status, in terms of available-to-usable power conversion efficiency, on those expected returns. Finally,
3. Realistic predictions of technological growth, and
4. the impact of that growth on the rate of investment returns.

Users would be able to manipulate the model to produce prediction data that compels an argument for a particular investment scenario. In particular, users would manipulate

1. invested capital, in service of the users' particular proposal, and
2. the rate of new-technology adoption, according to the unique business dynamics of the proposed organization.

As output, users would receive a graphical display of expected returns growth, highlighting the beneficial effect of "area under the curve" growth due to early investment and continual improvement. This graphical model output is designed considering the distinct psychological reactions to numbers comparison versus graphical area estimation; that is, people are more likely to estimate a filled area to represent greater benefits, contrasting with an unfilled line or a number-to-number comparison–both of which have a respectively decreasing psychological impact.

Additionally, the model should provide numerical outputs to ground the graphical output in detail. Both the initial power output returns and the integral of returns over time should be displayed with the graph of projections.

Analysis of Motivating Data

Before beginning development on the model, we assembled a number of data sets to compel our basic claims. Due to the number and complexity of factors that comprise the energy sector, we limited the scope of our research to a single distributor in a region of particular interest. California Independent System Operator (CAISO) is the only privately operated energy distributor in the Western United States and provides energy to 80% of consumers throughout California; making it one of the largest independent operators in the world. California's mild climate, undeveloped land area, and high year-round incidence of solar radiation make it strong candidate for large-scale dependence on solar power. What's more, the relatively progressive and wealthy state government makes California a powerful representation of the current sociopolitical outlook on alternative energies. These factors interact to make California a good model for analyzing the influence of solar power in the energy sector. CAISO's broad coverage of that market gives us a single point of reference for data we may consider to be representative of trends in the overall solar power market.

Fortunately CAISO makes great deal of real-time and historical data accessible to the public in easily consumable formats. Those sources from which we obtained the following data are listed at the end of this paper.

Claim 1: Current solar power production falls well short of meeting average energy demand

We have stated our core premise to be that solar power has failed to establish dominance over other energy sources or to completely meet energy demands at any time. To support this claim we consider energy demands in the domain of CAISO over two periods*:*

Historical: Annual peak demands spanning the past twenty years[1], and

Daily: Five minute average demands on a twenty-four hour interval[2].

Historical demand

Data from CAISO give the peak energy demands each year on the interval from 1998 to 2018 inclusive. These points are also listed with the month in which

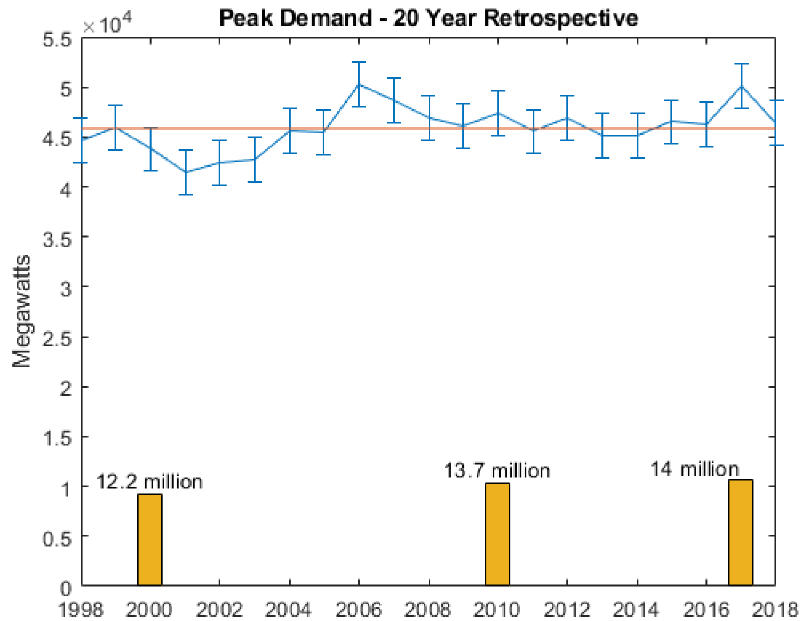

Figure 1: Historical power demand according to CAISO, and the portion of that usage due to homes.

they occurred, and those months are included as exclusion criteria for a *typical day* described in the subsection *Daily demand* on the following page.

We plot the historical peaks as a line of energy demand in Megawatts over years (figure 1 on the current page). We calculate statistics on the data and plot the average, as a horizontal line, and the standard deviation of each peak, as error bars on the peaks; this gives a helpful, if not rigorous, visual representation of the insignificance of fluctuations in the energy demand over the twenty year span. We present this to support the part of our claim that states that we know the average energy demands of the region of interest.

Further, we place this average peak demand behind a bar chart showing the average demand due to single-unit residences in the region–this in order to frame the vague Megawatt energy demands in terms interesting to the audience. To create that bar chart we obtain the total number of housing units, in years for which data are readily available, from the U.S. Census Bureau[16]; bars are plotted on the same axes from the previous chart. We calculate the bar height, thus the total energy demand of all homes for that year, by multiplying the number of homes by the average energy demand of a home in California[3]. The number of homes represented appears as a label above the bar chart.

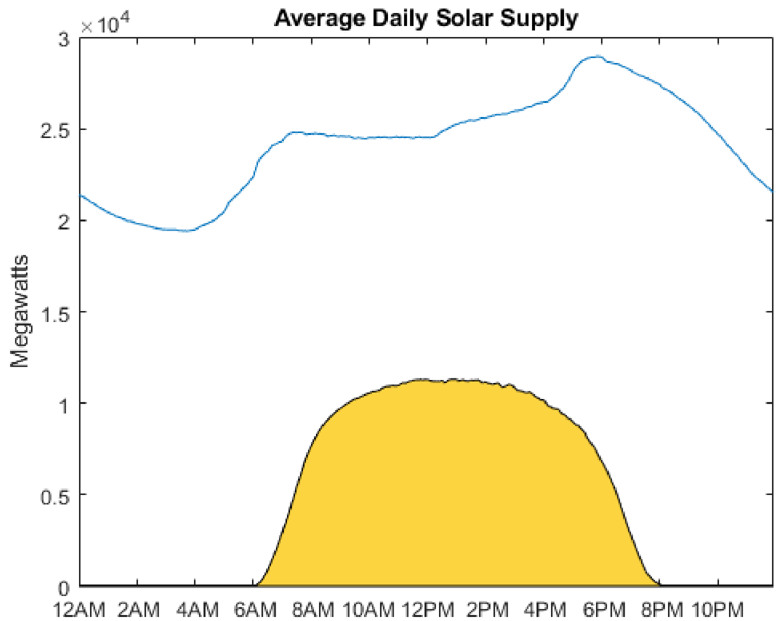

Figure 2: Daily power demand according to CAISO, and the power supplied by solar producers to meet it.

Daily demand

To limit the scope of this investigation we constrain the daily interval to a *typical* day, being one where weather conditions fall within the range of California's average climate[17]; the data service at the CAISO website allows daily averages to be downloaded for any day of the year for the current and last year, and the data are provided in the Comma-Separated-Values (CSV) format. We apply some restructuring transformations to the data in preparation for analysis, but do not change it meaningfully (e.g. by removing points).

Again plotting a line of Megawatts over time, we now scale the time axis to show one twenty-four hour interval (figure 2 on this page). Because the average daily demands are somewhat lower than the peak demands, the scale on the power axis has a smaller interval than that on the historical demand chart. This is an oversight that we think could be misleading in that the higher average demand appears to coincide with the highest peak demand; instead, the power axes between the two charts should be identical so that the inter-chart visual scale is identical to the inter-data scale.

Daily supply by solar power providers

On the chart of daily demand (figure 2 on the previous page) we overlay a plot of the daily supply from solar providers in CAISO's network. These data are available from CAISO in a format similar to the daily demand data and we manipulate and plot them in an identical manner. This chart serves to demonstrate the gap in solar infrastructure's ability to directly supply power during hours when sunlight is not available. We present this in the interest of making our proposal with integrity, in that we weigh our claims about solar power's benefits against the real difficulties that it presents. We see this chart as representing an opportunity for an industry of energy storage and delivery that will grow in partner with the solar power industry (and those of other alternative energies). The storage and delivery industry represents an extremely significant economic boon in the form of jobs and business development and, together with alternative energy production, may form the pillars of near-future national economic growth.

Yearly supply by solar power providers

Finally we present data that support the part of our claim that states that the supply of solar power falls well short of meeting power demands. Against the chart of daily demand we place overlapping areas whose heights represent, each for a successive year, the average supply of CAISO-distributed power that comes from solar producers (figure 3 on the following page). The areas overlap with most the most recent data behind more recent data so that the areas for each year occupy a portion of the maximum supplied amount. Solar production in successive years increased and as such the height of each area increases with successive years. In effect the areas show the growing supply capacity, with the height that each area protrudes showing the amount of growth in that year, and the largest area showing the highest supply capacity achieved. The composition of areas is displayed against the daily demand chart so that the growth in supply is visualized as a proportion of energy needs for the same region. In this way we demonstrate that the totality of installed solar infrastructure has failed to grow to meet even half of the average daily energy needs for the region. This demonstration ultimately compels the core premise of this paper.

For an optimistic turn, however, we use this same chart to show a major success for the solar industry: overlaying a line averaging the housing demand data from the subsection Historical demand shows that the working solar capacity in the region exceeded residential power demands as long ago as 2017. This is a significant argument to compel progress, rather than retreat, in response to our claims.

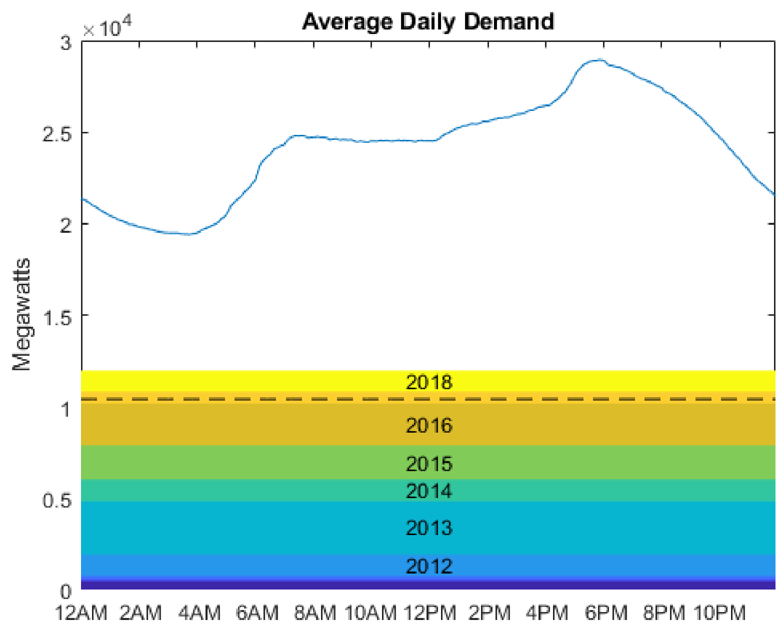

Figure 3: Daily power demand versus the total usable capacity as it grows by year. The height differential between two colored areas shows the amount of growth seen in that years. Dashed line is the average total demand by all homes in the region.

Claim 2: we can make realistic predictions of growth in solar technology performance

Predicting the growth of solar technology efficiencies is problematic for a number of reasons. First, we cannot reasonably estimate the likelihood of a breakthrough; these occur for reasons subject to chaos and cannot be inferred from historical trends. Less certain is whether we can predict the impact of changing sociopolitical attitudes and consequent governmental intervention, as exemplified by the space race and, before that, the nuclear arms race. There are these known powers that have great sway over the bringing of revolutions in technology, but they are outside the scope of our analysis. Additionally there are some technologies which exhibit highly nonlinear growth over longer time spans than we have access to for those in the solar power sector. Electricity was exploited, and even nontrivial communication systems such as the telegraph existed, among a relatively flat field of competing technologies for more than a century before the semiconductor revolution gave entry to the information age in a matter of a decade. Surely predicting such growth will expose us to the risk of overoptimism, which can be catastrophic for investments on the scale of an energy utility.

We claim that, despite these difficulties, we can make reasonable predictions of profitable development in the existing pipelines for photovoltaic semiconductor solar panels. We performed a survey of yearly reports of the state of the art and identified a highly regular trend that gives statistically powerful projections for at least twenty years hence. These reports are compiled by a consistent set of authors and published in the journal *Progress in Photovoltaics: Research and Applications.* They describe a method for performance evaluation and a summary of current research technologies measured by that evaluation.

We extracted data tables from several of these reports representing a period of fourteen years [5–13]. Given that many of the technologies reviewed did not perform adequately to be considered usable, we selected only the top fifteen percent of performers for consideration. We suggest that the other technologies are not likely to progress to the productization stage or will not see significant future development in their current form and so should not be considered in projecting that future development. We recognize, however, that this may be an extremely nuanced consideration and that a deep classification of those technologies should be made to identify potentially significant, if contextually different, improvement trends.

From the performance summary data we collated measures of each technology's efficiency in photovoltaic power production. The process by which a photovoltaic cell is outside the scope of this paper, but we will summarize in very short:

> Photonic energy incident on a photovoltaic material ionizes atoms in that material by elevating their valence electrons to higher quantum energy states. The structure of those materials is such that the

> now-disequilibrated electron potential diffuses in the material, thus an electrical current generated. A power collection circuit provides a constant potential gradient that decreases from the ionization center while providing a constant supply of electrons at the equilibrium energy state. In that way the solar cell is able to constantly produce electrical current under incident photonic radiation by restoring its photovoltaic material to an ionizable state while allowing it to be again ionized.

The efficiency we consider when evaluating the solar technologies herein is the proportion of usable energy produced by the cell to the radiation energy incident on that cell. We consider the average of all of the best fifteen percent of performers to be representative of the current state of the art; a chart of these can be seen in figure 4 on the next page.

We chose a quadratic fit for the projective curve to model these data. An exponential curve could also be made to fit, but we reject that because expecting exponential growth defies reasonableness in any but ideal conditions. We prefer the conservative view that favors under-investing rather than over-investing based on projections. An argument for our conservative position is made in the beginning of this section on the preceding page. The closeness of the quadratic fit is seen in the minute areas of disparity, shown in red in figure 4. Extending the efficiency scale to the interval $[0, 100\%]$ and extending the time scale out twenty years into the future, we see in a gradual increase in efficiency that we speculate to under-predict the real outcome (figure 5 on the next page); regardless hold that the conservative approach is the correct one given the scale of the projects at hand.

Modeling and Implementation

Having found a projection equation that fits the data and has adequate behavior we can begin to model the proposed interactive system. We accept two key parameters from the user that drive the interaction:

- U.S. Dollars invested in initial infrastructure, and
- an abstract rate of adoption, representing the proportion of the best technologies at any time that have been applied to the initial infrastructure.

As photovoltaic efficiency increases over time any given facility will consequently increase its performance according to the rate at which it implements those improvements. We include this proportional term to examine how a more or less aggressive approach to new technologies affects the lifetime return of an installation. Because most of the cost of a solar plant is in fact *not* in the solar cells themselves, we suggest that it is not unreasonable to consider continually upgrading those cells as they transit their maintenance and replacement lifecycle.

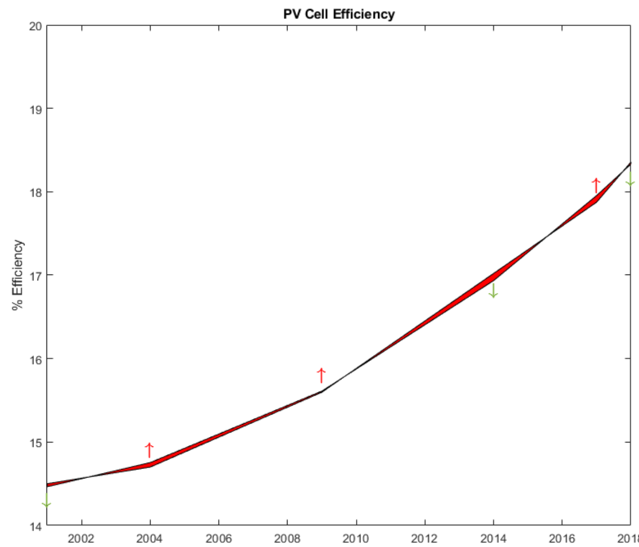

Figure 4: Average of best-performing photovoltaics over the years, compared with a quadratic projective curve for those data.

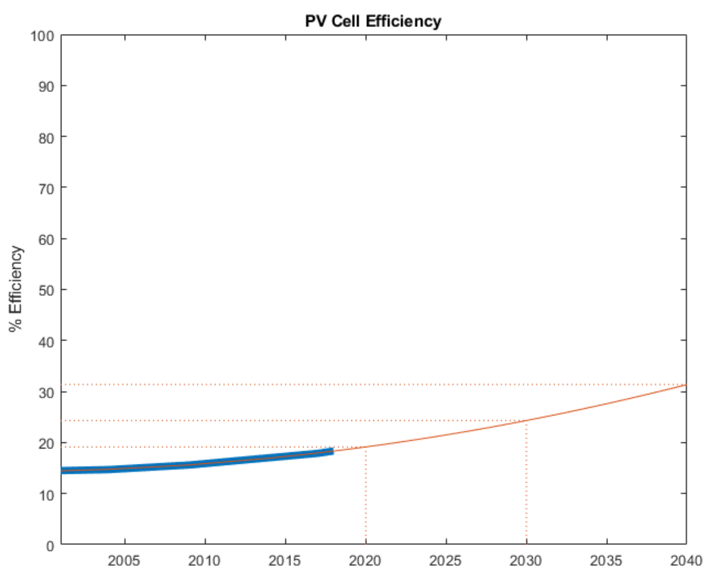

Figure 5: Projecting efficiency growth over twenty years.

By keeping the plant operating as close to state-of-the-art performance as possible, investors maximize on their investment in the energy handling, maintenence and operation, human resources, and general organizational investment that is the majority cost of the infrastructure.

Given the initial investment in dollars we find the initial capacity of the purchased plant according to the cost-per-watt scale factor. An in-depth survey of installations at different scales reveals a utility-scale cost of between \$1.11 and \$1.13 per watt[4]; we average this to give a scale factor of \$1.12 per watt, or 0.893 installed watts per dollar invested. This empirical figure does not exactly match our predicted value because our predictions are derived from an average of research technologies, whereas real installations will always use the technology with the best performance per cost at the time–which may perform better than our chosen average. Nevertheless we sustain that the average of top performers is more representative of future developments as technologies often alternately surpass each other throughout development, or a top performer may reach a plateau and be surpassed by all other competitors. By considering multiple differently-performing options we factor the potentially differing growth behavior of each and avoid overfitting to any one behavior. For this reason we maintain the efficiency curves so far developed, but add a constant bias to match our predicted value for 2018 to the value derived from the empirical reports. This ensures that our varied-option fit accurately predicts contemporary outcomes while more broadly considering the future.

We arrive at a dollars-to-watts conversion of

$$C = \frac{1 \text{ watt}}{\$1.12} \times D \times (\epsilon + 0.03668), \quad D > 0 \tag{1}$$

where C is output capacity, D is the user-controlled *dollars invested* parameter, and ϵ is cell efficiency. Projecting this conversion into the future, we let ϵ be the projective function of time, $\epsilon(t)$, where t is the year projected to:

$$C_{\text{ideal}}(t) = \frac{1 \text{ watt}}{\$1.12} \times D \times (\epsilon(t) + 0.03668) \tag{2}$$

We call this the *ideal projection* as it assumes that all efficiency gains are realized in the output capacity of the installation. In reality new developments will be adopted somewhat slower than they emerge as plant managers have to integrate them into the lifecycle of the installed cells. Thus we scale the ideal efficiency by the *adoption rate* parameter a and have the realized efficiency,

$$C_{\text{real}}(t) = \frac{1 \text{ watt}}{\$1.12} \times D \times (a \times \epsilon(t) + 0.03668), \quad 0 < a \leq 1 \tag{3}$$

Taking the interval from the year of installation T to the end of our projection, we estimate the total realized capacity of the plant as

$$C_{\text{lifetime}} = \frac{1 \text{ watt}}{\$1.12} \int_{T}^{2040} D\,(a\epsilon(t) + 0.03668)\,dt, \quad T < 2040 \tag{4}$$

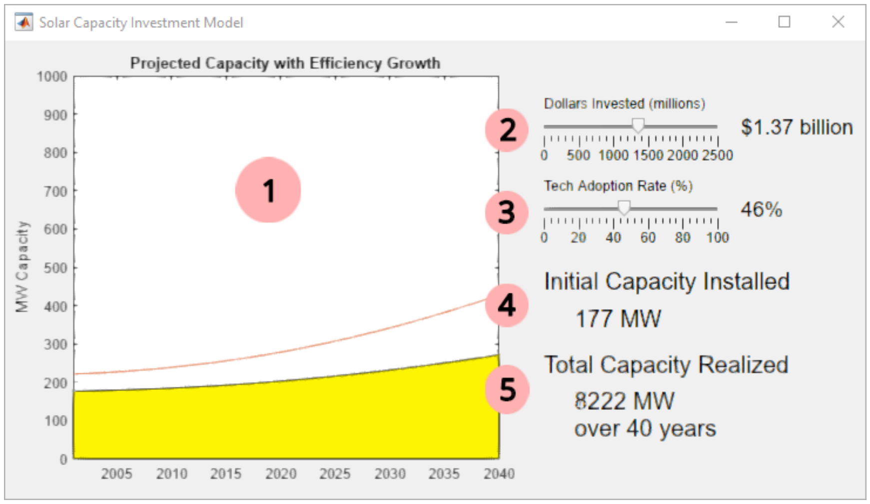

Figure 6: Single-document user interface window.

Implementing an interactive model in MATLAB

We used MATLAB 2018a by MathWorks[14] as the primary programming environment for data analysis, presentation, and modeling. For the interactive component we used MATLAB App Designer[15], which facilitates rapid layout of user interface components and greatly simplifies event handling for interactivity. The user interface comprises a single window (figure 6 on this page) with the following components:

1. A graph derived from the one in figure 5 on page 10, displaying the ideal projection as a line and the real projection as a filled area

2. A slider adjusting the *dollars invested* parameter in a domain constrained to empirically supported values where the model is likely to be valid

3. A slider adjusting the *adoption rate* parameter between 0 and 100%

4. A label displaying the initial capacity of the installation $C_{real}(2019)$ (equation (2) on the preceding page), assuming the installation is built in the present year; ultimately this should be a user supplied parameter

5. A label displaying the total projected output $C_{lifetime}$ (equation (4))

The control flow follows a straightforward event driven loop, illustrated in figure 7 on the next page. At startup the program loads the efficiency data and fits the curve for projecting efficiency.

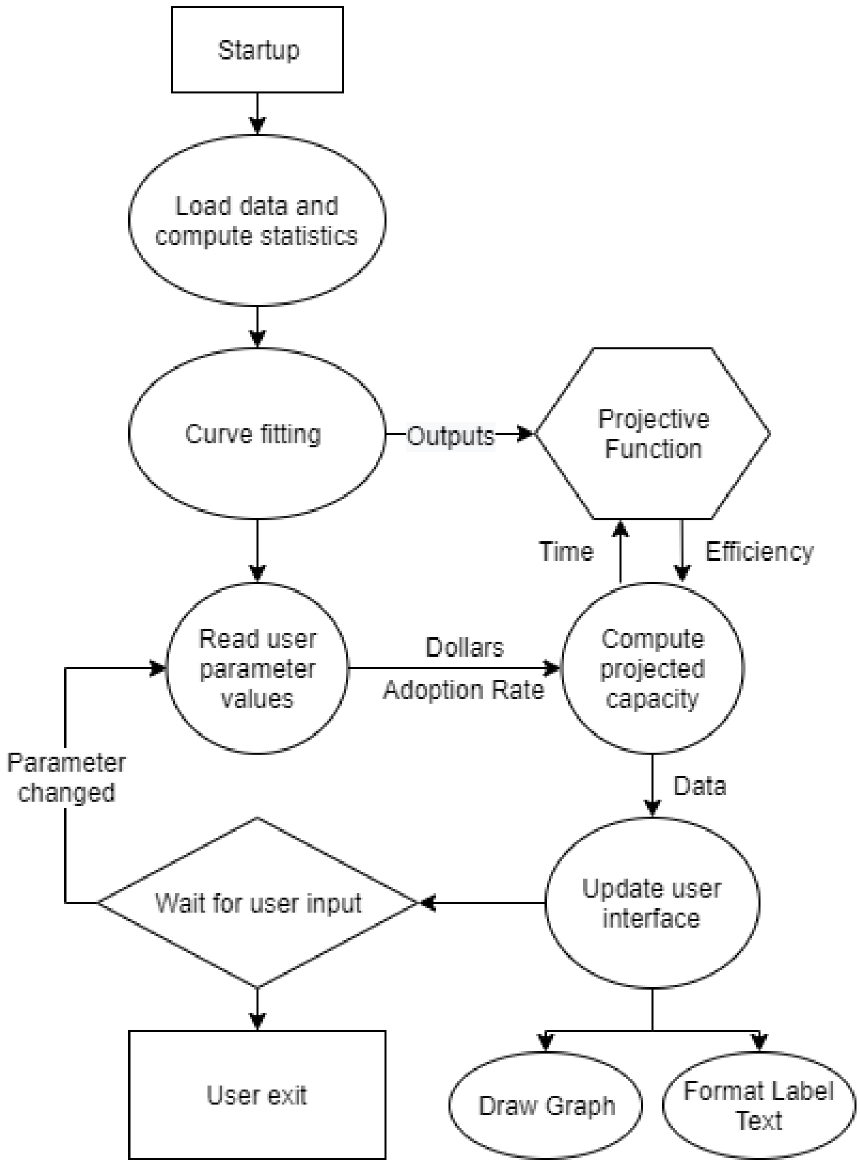

Figure 7: Interactive program control flow

Discussion

Overall the contents of this paper are simplified beyond the point of usefulness and we cannot draw any real conclusions from what we present here.

Regardless, we have succeeded at demonstrating elements of the scientific and engineering methods, despite our chosen problem domain being outside the scope of the project. We have so far (to whatever quality)

1. Named a domain of interest and formulated an issue, providing background to give the issue the context of cause and consequence

2. Conjectured about potentially extant dynamics contributing to the issue, drawing from the background to develop these

3. Speculated about interactions we might have with those dynamics to affect preferrable changes

4. Established a formal hypothesis, stating claims that we might support or reject with data

5. Gathered data that might justify those claims

6. Analyzed and presented those data to make our argument

7. Developed a theoretic model on the basis of our hypothesis and described it in mathematics

8. Developed a programmatic model to express those mathematics in a manipulable way so we might explore our hypothetical system

9. Analyzed our program and described its behavior

while further steps yet to be approached include

- Make predictions that may finally dismantle our argument and lead us to an alternative approach; for example we may explore real responses to our interactive model, making predictions about what inferences users might make from their experience and testing those predictions with real people

- Generate data from our model that have counterpoints in real empirical data sets, and apply statistical analysis to verify that our data reflect the behavior of real systems

- Review existing literature regarding the problem statement and seek to dismantle our argument prior to reinventing known solutions, especially worse versions of them

- Consult with experts in the problem domain to verify our observations, assumptions, methods, and conclusions

But we will leave these steps for another group.

References

References

[1] California ISO. *Peak Load History 1998 through 2018*. 2018. URL: https://www.caiso.com/Documents/CaliforniaISOPeakLoadHistory.pdf (visited on 11/20/2019).

[2] California ISO. *Todays Outlook*. 2019. URL: http://www.caiso.com/TodaysOutlook/Pages/default.aspx (visited on 11/20/2019).

[3] Eisenbach Consulting, LLC. *How Much Electricity on Average Do Homes in Your State Use? (Ranked by State)*. 2017. URL: https://www.electricchoice.com/blog/electricity-on-average-do-homes/ (visited on 11/20/2019).

[4] Ran Fu, David Feldman, and Robert Margolis. "U.S. Solar Photovoltaic System Cost Benchmark: Q1 2018". In: (2018), p. 62.

[5] Martin A. Green et al. "Solar cell efficiency tables (version 17)". In: *Progress in Photovoltaics: Research and Applications* 9.1 (Jan. 2001), pp. 49–56. ISSN: 1062-7995, 1099-159X. DOI: 10.1002/pip.361. URL: http://doi.wiley.com/10.1002/pip.361.

[6] Martin A. Green et al. "Solar cell efficiency tables (version 19)". In: *Progress in Photovoltaics: Research and Applications* 10.1 (Jan. 2002), pp. 55–61. ISSN: 1062-7995, 1099-159X. DOI: 10.1002/pip.428. URL: http://doi.wiley.com/10.1002/pip.428.

[7] Martin A. Green et al. "Solar cell efficiency tables (Version 31)". In: *Progress in Photovoltaics: Research and Applications* 16.1 (Jan. 2008), pp. 61–67. ISSN: 10627995, 1099159X. DOI: 10.1002/pip.808. URL: http://doi.wiley.com/10.1002/pip.808.

[8] Martin A. Green et al. "Solar cell efficiency tables (version 33)". In: *Progress in Photovoltaics: Research and Applications* 17.1 (Jan. 2009), pp. 85–94. ISSN: 10627995, 1099159X. DOI: 10.1002/pip.880. URL: http://doi.wiley.com/10.1002/pip.880.

[9] Martin A. Green et al. "Solar cell efficiency tables (version 36)". In: *Progress in Photovoltaics: Research and Applications* 18.5 (June 2010), pp. 346–352. ISSN: 10627995, 1099159X. DOI: 10.1002/pip.1021. URL: http://doi.wiley.com/10.1002/pip.1021.

[10] Martin A. Green et al. "Solar cell efficiency tables (version 39): Solar cell efficiency tables (version 39)". In: *Progress in Photovoltaics: Research and Applications* 20.1 (Jan. 2012), pp. 12–20. ISSN: 10627995. DOI: 10.1002/pip.2163. URL: http://doi.wiley.com/10.1002/pip.2163.

[11] Martin A. Green et al. "Solar cell efficiency tables (version 41): Solar cell efficiency tables". In: *Progress in Photovoltaics: Research and Applications* 21.1 (Jan. 2013), pp. 1–11. ISSN: 10627995. DOI: 10.1002/pip.2352. URL: http://doi.wiley.com/10.1002/pip.2352.

[12] Martin A. Green et al. “Solar cell efficiency tables(version 24)”. In: *Progress in Photovoltaics: Research and Applications* 12.5 (Aug. 2004), pp. 365–372. ISSN: 1062-7995, 1099-159X. DOI: 10.1002/pip.574. URL: http://doi.wiley.com/10.1002/pip.574.

[13] Martin A Green et al. “Solar cell efficiency tables (version 47)”. In: (2015), p. 10.

[14] MathWorks. *MATLAB*. 2019. URL: https://www.mathworks.com/products/matlab.html (visited on 11/20/2019).

[15] MathWorks. *MATLAB App Designer*. 2019. URL: https://www.mathworks.com/products/matlab/app-designer.html (visited on 11/20/2019).

[16] U. S. Census Bureau. *American FactFinder*. 2019. URL: https://factfinder.census.gov/bkmk/cf/1.0/en/state/California/HOUSING (visited on 11/20/2019).

[17] U.S. Climate Data. *Climate California - temperature, rainfall and average*. 2019. URL: https://www.usclimatedata.com/climate/california/united-states/3174 (visited on 11/20/2019).