

DEVELOPING A PV AND ENERGY STORAGE SIZING METHODOLOGY
FOR OFF-GRID COMMUNITIES

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Dedicated to my namesake and late grandfather, David Newcomb.

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ABBREVIATIONS

CES	Centralized Energy Sharing
ESS	Energy Storage System
GCPV	Grid Connected Photovoltaic System
GHI	Global Horizontal Irradiance
HOMER	Hybrid Optimization of Multiple Energy Resources (Software)
IES	Interconnected Energy Sharing
LLP	Loss of Load Probability
LPSP	Loss of Power Supply Probability
NSRDB	National Solar Radiation Database
PV	Photovoltaic
SAPV	Stand-alone Photovoltaic System
SOC	State of Charge
STM	State Transition Matrix
TMY	Typical Meteorological Year

GLOSSARY

Centralized Energy Sharing (CES)	An operating strategy for a SAPV where residential customers do not have individual batteries or solar panels but instead buy into a collective solar and battery system.
Grid-Connected Photovoltaic System (GCPV)	A Photovoltaic system which injects the solar electricity to a power utility grid network. Typically consists of two major components: the PV modules and inverter. Due to the ease of interconnection and small number of components involved, GCPV systems are more widely used especially in locations with a readily available utility grid network.
HOMER	A widely used, commercially available software for optimizing microgrids and distributed energy resources. The acronym stands for 'Hybrid Optimization of Multiple Energy Resources.'
Interconnected Energy Sharing (IES)	An operating strategy for a SAPV where each house is connected to an energy infrastructure which allows for energy trading. Energy trading allows for less excess generation to be wasted and a secondary source of back up power, however, the energy infrastructure must be created.
Isolated Self Consumption	The conventional operating strategy for a SAPV where each house is disconnected from any energy infrastructure and can only supply its loads from its own solar power. Using this operating strategy, excess generation is typically wasted and costly, polluting generators must be used for providing back up energy.

Loss of Power Supply Probability (LPSP)	A loss of load occurs whenever the system load exceeds the available generating capacity. The overall probability that there will be a shortage of power (loss of supply) is called the Loss of Power Supply Probability. It is usually expressed in terms of days per year, hours per day, or as a percentage of time. Similar terms include Loss of Load Probability (LOLP), Loss of Power Probability (LOPP), and Load Coverage Rate (LCR).
Stand-alone Photovoltaic System (SAPV)	A Photovoltaic system which is used to directly power electrical loads without connecting to the conventional power grid. An SAPV system typically consists of PV modules, charge controller, batteries and an inverter. There is typically no back-up power to meet the load demand during events with no PV generation such as on rainy or cloudy days, after dark, or during system failure. For this reason, reliability of electricity supply is given top priority in the system design of a SAPV.

ABSTRACT

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Combining rooftop solar with energy storage for off-grid residential operation is restrictively expensive. Historically, operating off-grid requires an 'isolated self-consumption' operating strategy where any excess generation is wasted and to ensure reliability you must install costly, polluting generators or a large amount of energy storage. With the advent of Blockchain technology residents can come together and establish transactive microgrids which have two possible operating strategies: Centralized Energy Sharing (CES) and Interconnected Energy Sharing (IES). The CES strategy proposes that all systems combine their photovoltaic (PV) generation and energy storage systems (ESS) to meet their loads. IES strategy establishes an energy trading system between stand-alone systems which allows buying energy when battery capacity is empty and selling energy when battery capacity is full. Transactive microgrids have been investigated analytically by several sources, none of which consider year-round off-grid operation.

A simulation tool was developed through MATLAB for comparing the three operating strategies: isolated self-consumption, CES, and IES. This simulation tool could easily be incorporated into existing software such as HOMER.

The effect of several variables on total cost was tested including interconnection type, initial charge, load variability, starting month, number of stand-alone systems, geographic location, and required reliability.

It was found that the CES strategy improves initial cost by 7% to 10% compared to the baseline (isolated self-consumption) and IES cases in every simulation. The IES case consistently saved money compared to the baseline, just by a very small amount

(less than 1%). Initial charge was investigated for March, July, and November and was only found to have an effect in November. More research should be done to show the effect of initial charge for every month of the year. Load variability had inconsistent results between the two geographic locations studied, Indianapolis and San Antonio. This result would be improved with an improved load simulation which includes peak shifting. The number of systems did not have a demonstrable effect, giving the same cost whether there were 2 systems or 50 involved in the trading strategies. It may be that only one other system is necessary to receive the benefits from a transactive microgrid. Geographic locations studied (Indianapolis, Indiana; Phoenix, Arizona; Little Rock, Arkansas; and Erie, Pennsylvania) showed a large effect on the total cost with Phoenix being considerably cheaper than any other location and Erie having the highest cost. This result was expected due to each geographic location's load and solar radiation profiles. Required reliability showed a consistent and predictable effect with cost going down as the requirement relaxed and more hours of outage were allowed.

In order to accomplish off-grid operation with favorable economics it is likely that a system will need to reduce its reliability requirement, adopt energy saving consumption habits, choose a favorable geographic location, and either establish a transactive microgrid or include secondary energy generation and/or storage.

Keywords: Energy Sharing, Photovoltaic, PV Sizing, Energy Storage, Loss of Power Supply Probability, PV Utilization, Load Variability, Transactive Microgrid, Blockchain

1. INTRODUCTION

This thesis will be organized as follows: 'Chapter 1: Introduction' introduces SAPV systems and energy sharing strategies, states the problem, expresses the significance of the study, and outlines the scope and limitations; 'Chapter 2: Literature Survey' compares GCPV and SAPV systems, describes the major components of SAPV systems, provides background information on how the methodology is developed such as how geological conditions can be simulated, how residential load profiles can be simulated, and how the sizing of SAPV systems can be optimized; 'Chapter 3: Methodology' explains the research design for analyzing if it is beneficial for residential customers to establish interconnected communities, establishes the specific cases that will be investigated, explains input variables and where their information is obtained from, and outlines how results will be analyzed; 'Chapter 4: Results' analyzes the results gathered from applying the methodology described in Chapter 3 and discusses the implications of the data; finally, 'Chapter 5: Conclusions' reviews the work that was accomplished and summarizes the major findings.

1.1 Stand-Alone Photovoltaic Systems (SAPV)

A Stand-Alone Photovoltaic System (SAPV) employs solar panels and energy storage to fulfill load requirements without being connected to a conventional grid system. If the cost of generating and storing electricity is less than the cost of electricity from the grid, consumers and small businesses can save money with this approach. Although current prices restrict SAPV feasibility, "the cost of PV-generated and stored energy is declining, while retail power prices are on the rise" [1, 2]. Sometimes, an SAPV makes sense in rural areas where it is difficult and expensive to extend existing power lines to connect with the grid (which can cost the customer between

\$15,000 and \$50,000 per mile) [3]. The high expense is due to the large amount of storage required to ensure sufficient reliability going off-grid. Studies which attempt to optimize solar and storage for off-grid residential applications have suggested it is not currently economical [4–7]. The conventional operating strategy for going off-grid, isolated self-consumption, requires that any excess generation is wasted and for back-up energy the most cost effective method is costly, polluting generators. To remain zero emission, large amounts of additional storage are required just to improve reliability by a fraction.

A new method for going off-grid, transactive microgrids, has been enabled with the advent of 'Blockchain'. It is now possible to centrally store PV and ESS known as Centralized Energy Sharing (CES) or distribute PV and ESS and establish a trading system known as Interconnected Energy Sharing (IES), connecting otherwise stand-alone systems. According to Renewable Energy World [8] "Blockchain makes a new energy sharing economy possible, one that facilitates an open exchange of power between homes, with all transactions recorded through a decentralized ledger. This will represent a fundamental change in the way we generate, use and distribute energy for the better. Its promise will empower all of us to determine the impact our homes have on our climate." Hahn [9] demonstrates how transactive energy exchanges can be implemented on the Ethereum blockchain. To be clear, Blockchain technology enables the transactive microgrid which will be investigated but is not the subject of this research.

1.2 Centralized Energy Sharing (CES)

In this operating strategy, solar panels and energy storage are 'centrally stored' within an off-grid residential microgrid meaning that customers do not have individual batteries to monitor but a collective battery system. In this system all loads are summed and considered as one, energy trades are internal, and if the energy storage is depleted then every customer is without power.

1.3 Interconnected Energy Sharing (IES)

In this operating strategy, solar panels and energy storage are distributed throughout the community, but a microgrid is established which allows for customers to buy and sell their energy. Habib [10] proposed an 'interconnected sharing mode' where residential customers can exchange PV power to supply their electrical loads in the case that the micro-grid switches to islanded mode due to large scale power outage or blackout. In a study of 10 houses the inter-connected sharing case supplied the most load for 5 out of the 10 houses, 3 houses preferred isolated self-consumption, and 2 houses achieved the same load met under either operating mode. The author states "the interconnected energy sharing case produces only slightly better individual results than the isolated case. However, most importantly, it also lead to a 44% reduction in the total size of ESS required." Habib also states that "isolated self-consumption is only attractive if the size of the PV associated with each house is large relative to the consumption, but most houses, at least in winter, do not get much power from their local PV generation and their loads are lost. [11]" While Habib's proposal is for grid-connected customers which are disconnected from the grid due to isolation or blackout, this thesis proposes allowing islanded residential customers to share their stored energy amongst each other year-round without connecting to the main grid. Being able to sell energy when the battery is at capacity and buying energy when battery is depleted should increase reliability and reduce the individual costs associated, however, there are costs to interconnect such a community.

1.4 Problem Statement

The idea of a 'transactive or connected neighborhood' for a residential micro-grid has been investigated analytically by several sources, none of which use conventional SAPV sizing strategies or consider off-grid operation [12–16]. The gap in literature this research fills is to propose a sizing methodology for off-grid transactive microgrids so that operating strategies (isolated self-consumption, CES, and IES) can be com-

pared. A MATLAB program will be developed for comparing the costs and reliability of each operating strategy.

The problem this thesis seeks to solve: What type of SAPV energy sharing strategy provides the lowest total cost? For each energy sharing strategy, how does initial battery charge, load variation, starting month, number of SAPV systems, geographic location, and required reliability affect total cost?

The goal of this thesis research is to develop a tool for comparing energy sharing tactics between SAPV systems (isolated consumption, CES, and IES) and then use that tool to compare operating strategies and show the effect of relevant variables on total cost.

Specific objectives include:

- Develop a tool (MATLAB program) which compares 3 operating strategies for SAPV systems (isolated self consumption, CES, IES).
- Simulate the tool considering the effect of initial battery charge, load variability, starting month, number of SAPV systems, geographic location, and required reliability on energy storage required and total cost.
- Compare results each operating strategy to determine how effectively energy sharing reduces initial cost in SAPV systems.

There may be other operating strategies to consider, but they will be similar in style to either the IES or CES case. For example, the systems may be connected like IES but operate with the objective of only allowing equitable trades or the systems may be connected like CES but operate with restrictions which restrict one system from taking advantage of the others.

The variables initial charge, geographic location, required reliability, and starting month were chosen as a natural progression from the software development. Looking at isolated SAPV systems it made sense that the same variables would be important in interconnected systems. Load variation was investigated because this is what makes energy trading worthwhile. If every system has the same load and PV generation than

there will not be any instances where it is beneficial for them to trade. Finally, the number of SAPV systems was chosen because it was thought that with more systems more trades would occur and the benefit of establishing a transactive microgrid would increase. Component specifications (PV rating, PV cost, battery efficiency, battery cost) could have been investigated to show how these specifications must be improved to make transactive microgrids economical, but it made sense to start with current technologies.

1.5 Significance of the Study

The purpose of this section is to identify the significance of the study.

This study progresses the research of sizing SAPV systems, sharing economies for the grid, establishing infrastructure between SAPV systems, and the effect of load variation on SAPV sizing.

The implementation of this study will improve off-grid neighborhood planning, encourage SAPV energy sharing research, and identify the best (least expensive) energy sharing strategies.

Indirectly, this study contributes to the progress of geological simulation for SAPV sizing and application of Markov models.

The model developed can be used to determine PV, ESS, and interconnection pricing goals that will make off-grid transactive neighborhoods competitive with utility pricing.

In the field of SAPV systems this study proposes a new way of addressing the lack of an energy market. It's important to improve solar irradiation modeling, PV and ESS efficiency, and electric distribution, but there may be a more innovative approach to solving this problem such as establishing energy infrastructure.

At later stages, the model developed in this study can be used to plan energy infrastructure between existing/theoretical SAPV systems, study the effect of load variation on IES scenarios, and find ideal situations for implementing case studies.

This model could be incorporated into existing software such as HOMER, which was investigated but did not have the capability to simulate interconnected energy sharing.

1.6 Scope and Limitations

The purpose of this section is to identify the scope and limitations of the research.

This research is limited to studying SAPV systems. The problems presented will not likely be important when applied to GCPV systems. SAPV systems present unique challenges in reliability and design that do not apply to GCPV systems which have back-up power provided by the grid.

For this research, systems connected to an energy trading infrastructure that would otherwise be off-grid are also referred to as SAPV systems.

This research does not consider the social and political parameters that can be taken into consideration when designing an SAPV system or microgrid.

This research does not consider the technical aspects of choosing a location for the solar panel and ESS. There are some scenarios in this research that recommend a large amount of solar panels or ESS that a typical residential customer would not be able to fit on their property.

In this study, the term 'energy sharing' is used to discuss different operational strategies. This is the term used by Habib [10] and is not to say that the residential customers will be expected to share their energy without any compensation. Instead the residential customers will trade, buy, and sell energy using the 'energy sharing' operational strategy. The specifics of price, equity, and policy regarding these trades will not be discussed in this research.

The model excludes the effect of temperature and clearness index in the PV output simulation, discharge/charge rate in the energy storage simulation, and lifetime or degradation of any of the parts.

The model assumes that all IES SAPV systems will have the same number of solar panels and receive the same solar irradiation. This is not a likely scenario but avoids additional variability, questions of equity, and situations where an SAPV system has no power generation. In the future, issues of inequality must be modeled and addressed.

The study does not intend to replace the existing power system infrastructure. As stated before, residential solar power is often more expensive than that provided by a utility and there is already a reliable, cheap electricity supply available just about anywhere in the United States. However, considering the number of homeowners currently off the grid, emerging markets worldwide, and the cost of extending power lines, there may be some systems which will benefit from energy sharing. In particular, IES and CES strategies will be practical for isolated microgrids which have no access to an existing national grid.

The model used in this paper is limited to hourly simulations. A higher time resolution of a minute or second is desired for more accurate simulation of PV and ESS performance. For instance, with a smaller time step the model could include charge/discharge rate of the battery, specific appliance end-uses, and charge controller behavior.

Finally, the scope of this thesis is limited to SAPV systems in the United States. Component specifications, residential load profiles, and geological conditions may not be relevant for another geographical location.

2. LITERATURE SURVEY

The purpose of this chapter is to compare grid-connected and stand-alone PV systems, describe major components of SAPV systems for use in modeling, and investigate methods for simulating geological conditions and residential load profiles and optimally sizing SAPV systems.

2.1 Grid-Connected PV vs. SAPV

Fundamentally, solar energy from the sun is converted to electricity for use in our homes via the photovoltaic (PV) effect. This electricity can be implemented using either a Grid-Connected Photovoltaic (GCPV) system or a Stand-Alone Photovoltaic (SAPV) system. A GCPV system is an independent decentralized power system that is connected to an electricity transmission and distribution system (referred to as the electricity grid). An SAPV produces power independently from the utility grid; hence, they are said to be stand alone [17]. A GCPV system typically consists of two major components i.e. the PV modules and inverter while an SAPV system consists of PV modules, charge controller, batteries, and inverter. GCPV systems offer a distinct advantage in having energy back up to meet the load demand whenever the system fails. As a result, the design of GCPV systems are often less critical when compared to SAPV systems because the reliability of electricity supply for a particular location is often not an issue [18]. However, SAPV systems are becoming increasingly viable and cost-effective in remote locations where there is no readily available utility grid network, where there is very high yearly solar radiation, or when the cost of producing and storing energy is less than the cost of buying from the utility [18–21].

Nick Rosen, author of "Off the Grid: Inside the Movement for More Space, Less Government, and True Independence in Modern America" [22], estimated in 2010

that at least 750,000 US households are self-reliant in producing one of their utilities (water, electricity, sewer, natural gas, and other services). Home Power Magazine [23] estimated in 2006 that at least 180,000 US households operate without the assistance of any public utility service. Major reasons for wanting an off-grid system where the grid is available are energy independence, green living, and saving money. Owners of off-grid systems are not subject to rate increases, blackouts, or the terms and policies of the local utility. System owners can also rest assured that the energy they use is produced in a clean, sustainable manner.

Be aware though, once off-grid, you must now take on the duties of the utility you sought independence from. First of all, making your own electricity is expensive, and it's unlikely that installing an SAPV will provide you with cheaper electricity unless the resident has very high solar irradiation, generous incentives, high utility rates, existing solar and energy storage or some combination of the above. Also, system maintenance and troubleshooting are serious, ongoing problems. Most batteries will need to be replaced every 5-15 years. A battery is only 90% efficient at its best causing large amounts of energy waste [24]. Another serious drawback is wasted surplus energy. When a GCPV system makes more electricity than the homeowners use, the surplus is sold to the utility for an energy credit which can be exchanged for money or energy when needed. In contrast, an SAPV must either use the surplus or waste it. Usually the inverter automatically turns off so that the energy is never generated in the first place. Of course, the major drawback of SAPV systems is ensuring reliability. A GCPV system can always rely on the utility for backup power but an SAPV system must size their PV and energy storage so that their load is met reliably throughout the year.

This is specifically the area which this research seeks to improve. SAPV systems waste energy and money by not being able to sell back to the grid and they have no access to backup power because they are not able to buy energy from the grid. If energy infrastructure could be established which enables systems to sell power when their batteries are full and buy power when their batteries are empty, this would

increase their reliability and improve their utilization of solar energy, theoretically reducing total cost depending on the cost to implement the energy infrastructure. This energy infrastructure could be expanded to include load control or electric vehicle storage for further improvement of reliability and reduction of cost. It might be the case that there are several SAPV systems too far from the standard utility grid to become GCPV or that by establishing energy infrastructure they succeed in establishing a lower energy rate than if they were connected to the grid. These SAPV systems could save money by establishing an energy infrastructure amongst themselves instead of connecting to the grid or going alone, although they will not be able to sell or buy from the standard grid and the combined initial capital cost will likely require a company to bring the community together.

2.2 Components of SAPV Systems

Because of the stochastic nature of the sun (variability introduced from day and night cycle plus clouds) the power output from solar energy is not predictable or linear. Therefore, energy storage resources such as an electrochemical battery, flywheel, and ultracapacitor, or a generator are required to meet the load demand when there is a shortage of available energy from the renewable source [25]. A typical SAPV consists of PV generation, battery storage, charge controller, inverter, and a load as illustrated in Figure 2.1. Often, a generator is used to improve reliability in winter months or when energy storage is low but will not be considered in this research. To help understand the proposed energy infrastructure these components will be investigated further: solar panels, energy storage devices, charge controllers, inverters, and residential load profiles.

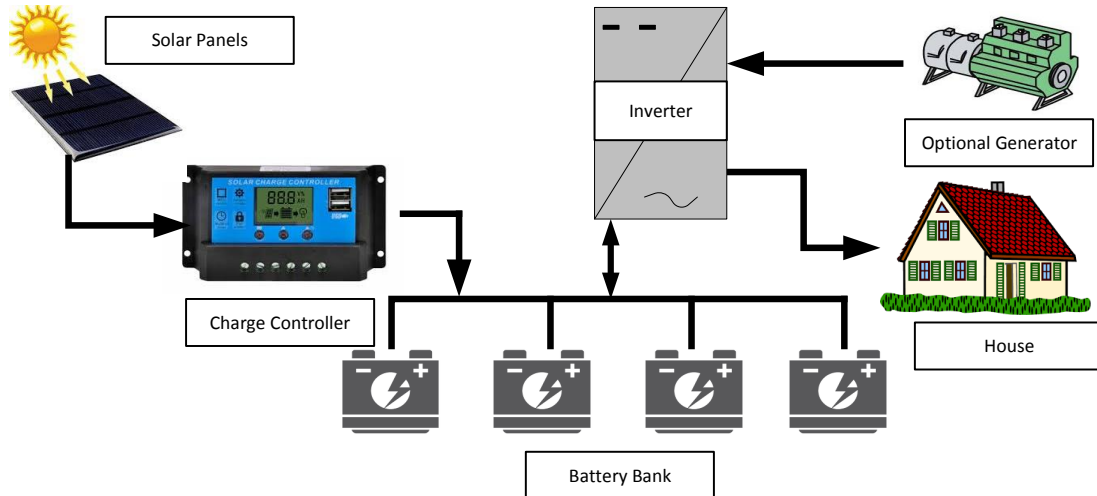


Figure 2.1. Typical components of an SAPV.

2.2.1 PV Panels

PV panels or solar panels convert sunlight into direct current (DC) electricity. PV panels are made of many silicon solar cells, which act as semiconductors. When photons from sunlight strike the surface, electrons flow due to the photoelectric effect.

2.2.2 Energy Storage System (Battery)

Because solar panels only generate electricity during the day when the sun is shining, this energy must be used instantaneously or stored in an energy storage system. The most common energy storage device for residential applications is the battery.

A battery is a device that converts the chemical energy contained in its active materials directly into electric energy by means of an electrochemical oxidation-reduction (redox) reaction. While the term "battery" is often used, the basic electrochemical unit being referred to is the "cell." A battery consists of one or more of these cells,

connected in series or parallel, or both, depending on the desired output voltage and capacity [26].

2.2.3 Charge Controller

The battery's current and voltage are controlled by a charge controller in order to increase battery life, improve performance and protect the battery from damage due to deep discharging. Using a good charge controller, for example, a Pulse Width Modulation (PWM) with state-of-charge calculation algorithms, the same battery exposed to the same charge/discharge cycles can have a much higher lifetime than one using a bad charge controller with incorrect settings [27].

2.2.4 Inverter

Because the U.S. electrical grid uses AC electricity and solar panels create DC electricity, an inverter must be used. Along with converting DC to AC power, inverters provide ground fault protection and monitor system stats, including voltage, current, energy production, and maximum power point tracking [28].

2.2.5 Residential Load Profiles

A residential load profile shows yearly energy usage for a residential customer either historically or simulated based on geographical location, appliances, building characteristics, type of heating, type of lighting, and occupant behavior among other factors. These load profiles are useful for accurately forecasting load, planning networks, and sizing renewable generation. Pairing this information with the expected power output of solar panels is a way of simulating the expected energy an energy storage device or the grid will need to supply. Figure 2.2 shows a sample residential load profile, demonstrating some of the numerous factors that can be considered. This load profile is typical, with a minor peak in the morning when residents are typically

waking up and preparing for work, a larger peak in the afternoon when residents are returning from work and preparing for bed, and it usually bottoms out when residents are sleeping and at work. Note: A load profile can vary drastically with new technology such as electrical vehicles and energy storage or with different occupant behavior such as vacation or odd-working hours.

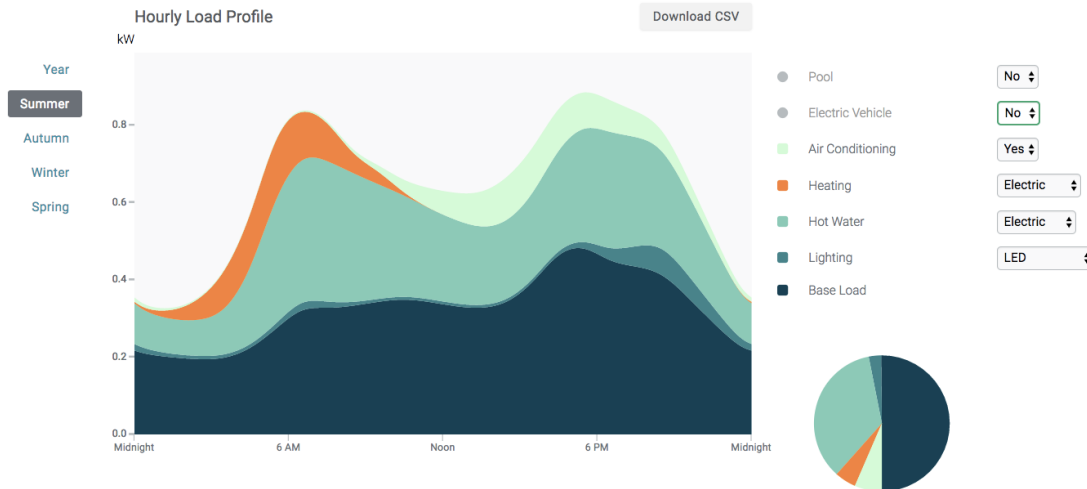


Figure 2.2. An example of an estimated energy load profile in summer for a residential house in Stanford, California with air conditioning, electric heat, and LED lighting [29]

2.3 Simulation of Geological Conditions

Solar radiation data is required to determine the availability and magnitude of solar energy at a specific site. Geologic conditions, including solar radiation, clearness index, and ambient temperature are always changing. Therefore, a long-term analysis of solar energy resource should be performed at the start of any project for accurate sizing of components [30].

Two methods for simulating geological conditions include: Time-series simulation and Statistical simulation.

2.3.1 Time-series Simulation

Time-series simulation relies on historical weather data such as hourly solar radiation, wind speed, and ambient temperature to 'estimate' or 'recreate' solar radiation conditions for a time period. This weather data can usually be obtained from the Internet or from local meteorological stations for any US location. For instance, the National Solar Radiation Database (NSRDB) has a comprehensive collection of meteorological and solar data across the United States and a growing list of international locations that is publicly available at no cost to the user [31].

Practically measured data is the most accurate but not always readily available, which is mainly due to the initial investment and maintenance cost of the measuring instruments and relevant recorders. In reality, the transient solar irradiance at any location, with the unit of W/m^2 , keeps changing throughout the daytime, which mainly attributes to the movement of the earth and the chaotic effect of the atmosphere. There is barely any effective way to accurately estimate or predicate transient solar irradiance except practical measurement [32]. Therefore, any method used to simulate geological conditions should be based on field measurements and not on global simulation, monthly averages, or extrapolated from far away sites.

One method for developing synthetic solar data from historical data that has been around for many years is the use of a Markov model. U. Amato [33] showed that irradiation sequences are not stationary, both in the mean and in the variance, and can thus be modeled by Markovian and Fourier concepts.

Weissbach [4] created a Markov model consisting of 288 (24 hours x 12 months per year) state transition matrices to generate synthetic solar data for analysis.

Chamola [34] generally improved Weissbach's model by introducing day-level weather correlations that are critical for dimensioning high-reliability systems.

2.3.2 Statistical Simulation

Sometimes, hourly records of meteorological variables do not exist. In this case, synthetic weather data can be generated from the monthly-average values of the meteorological data or the weather data can be extrapolated from a nearby site by making necessary adjustments [30].

Because this thesis does not require a case-study for a specific location without hourly data, locations can be chosen so that reliable, long-term, hourly weather data is freely available. Thus, geological conditions will be simulated using the Time-Series method and statistical methods will not be further explained.

2.4 Modeling PV and ESS Performance

The purpose of this section is to outline how PV and ESS Performance can be modeled for use in developing the methodology.

Table 2.1 shows various equations which could be used for estimating power generation from a solar PV module. Most of them are complex and require year-round temperature data. Of particular interest for this study is equation 21 in Table 2.1. The symbol df , known as the de-rating factor, is used to estimate the loss in efficiency due to different factors such as wiring losses, soiling of the panels, shading, snow cover, and aging. This factor can be used to estimate temperature related effects to simplify the equation. Looking at Table 2.2 and 2.3, removing temperature considerations will greatly simplify the model. There will be no need to estimate cell temperature of the solar module and the efficiency of the module can just be taken as the reference efficiency. This is desirable for this research because the goal is to develop an initial estimate, not to do an in-depth case study.

Table 2.4 shows various correlations for simulating battery state of charge. An equation similar to the first equation in this table was chosen due to its simplicity and variable choice and is discussed in more detail in section 3.4.2.

Table 2.1. Various equations for estimating power generation from a solar PV module [35]. Sources and variables are stated within the reference.

Sr. No.	Model
1.	$I_{mp} = [I_{mp,ref} + \mu_I (T_{PV} - T_{PV,ref})] \left(\frac{G_T}{G_{ref}}\right)^{c_1}$ $V_{mp} = \frac{V_{mp,ref}}{1 + \mu_V \ln\left(\frac{G_T}{G_{ref}}\right)} \left(\frac{T_{PV,ref}}{T_{PV}}\right)^{c_2}$
2.	$P_{mp} = G_T (c_1 + c_2 \times G_T + c_3 \times T_a + c_4 \times V)$
3.	$V_{mp}(G_T, T_{PV}) = V_{mp,ref} + c_1 \ln(G_{norm}) + c_2 [\ln(G_{norm})]^2 + \mu_V (T_{PV} - T_{ref})$
4.	$I_{mp}(G_T, T_{PV}) = c_3 + G_{norm} [I_{mp,ref} + \mu_I (T_{PV} - T_{ref})]$ $V_{mp}(T_{ref}) = V_{mp} - \mu_V (T_{PV} - T_{ref})$ $I_{mp}(T_{ref}) = I_{mp} - \mu_I (T_{PV} - T_{ref})$
5.	$V_{mp} = V_{oc} \left[1 - \left(\frac{c_1}{V_{norm}}\right) \ln c_2 - \frac{R_s I_{mp}}{V_{oc}} (1 - c_2^{-c_1}) \right]$ $c_1 = \frac{c_2}{c_2 + 1}$ $c_2 = V_{norm} + 1 - 2 \left(\frac{R_s I_{mp}}{V_{th}}\right)$
6.	$I_{mp} = I_{sc} (1 - c_2^{-c_1})$ $P_{mp} = c_1 G_T + c_2 T_{PV} + c_3 [\ln(G_T)]^x + c_4 T_{PV} [\ln(G_T)]^x$
7.	$P_{mp} = \frac{G_T}{G_{ref}} [P_{mp,ref} + \mu_P (T_{PV} - T_{ref})]$
8.	$P_{mp} = c_1 G_T + c_2 T_a + c_3 [\ln(G_T)]^x + c_4 T_a [\ln(G_T)]^x$ $+ c_5 G_T \exp(x_1 + x_2 V) + c_6 G_T [\ln(G_T)]^x \exp(x_1 + x_2 V)$
9.	$I_{mp} = (c_1 G_{norm} + c_2 G_{norm}^2) [I_{mp,ref} + \mu_I (T_{PV} - T_{ref})]$ $V_{mp} = V_{mp,ref} + c_3 N_s V_{th} \ln(G_{norm}) + c_4 N_s \{V_{th} \ln(G_{norm})\}^2 + \mu_V (G_{norm}) (T_{PV} - T_{ref})$
10.	$V_{mp}(T_{PV}) = V_{mp,ref} + \mu_V (T_{PV} - T_{ref})$ $I_{mp}(G_T, T_{PV}) = \frac{G_T}{G_{ref}} [I_{mp,ref} + \mu_I (T_{PV} - T_{ref})]$
11.	$P_{mp} = \frac{G_T}{G_{ref}} [P_{mp,ref} + \mu_P (T_{PV} - T_{ref})]$
12.	$P_{mp} = \frac{0.008 \times G_T^2}{G_{ref}} [P_{mp,ref} + \mu_P (T_{PV} - T_{ref})]$
13.	$P_{mp} = \frac{G_T}{G_{ref}} [P_{mp,ref} + \mu_P (T_{PV} - T_{ref})] - [P_{mp,ref} \times cf \times \left(\frac{G_{ref} - G_T}{G_{ref} - 200}\right)]$
14.	$P_{mp} = \frac{G_T}{G_{ref}} [P_{mp,ref} + \mu_P (T_{PV} - T_{ref})] - P_{mp,ref} \times cf \times \left[1 - \left(1 - \frac{G_T}{200}\right)^4 \right]$
15.	$I_{PV} = [I_{ref} + \mu_I (T_{ref} - T_{PV})] \left[\frac{G_{ref}}{G_T}\right]$ $V_{PV} = [V_{ref} + \mu_V (T_{ref} - T_{PV})] \left[1 + \frac{k_B T_{PV}}{q} \ln\left(\frac{G_{ref}}{G_{PV}}\right) \right]$
16.	$I_{PV} = \frac{G_T}{G_{ref}} [I_{ref} + \mu_I (T_{PV} - T_{ref})]$ $V_{PV} = V_{ref} - R_s (I_{PV} - I_{ref}) + \frac{k_B T_{PV}}{q} \ln\left(\frac{G_T}{G_{ref}}\right) + \mu_V (T_{PV} - T_{ref})$
17.	$I_{PV} = I_{ref} + I_{sc,TS} \left[\frac{I_{ref} I_{sc}}{I_{sc,TS}} - 1\right] + \mu_I (T_{PV} - T_{ref})$ $V_{PV} = V_{ref} - R_s (I_{PV} - I_{ref}) - [cf \times I_{PV} (T_{PV} - T_{ref})] + \mu_V (T_{PV} - T_{ref})$
18.	$P_{mp} = c_1 \times G_{ref} [1 + c_2 (T_{PV} - T_{ref})]$
19.	$P_{mp} = c_1 [1 + c_2 (T_{PV} - T_{ref})] (c_3 + G_{ref})$
20.	$P_{str1} = P_{str,ref} \frac{X - S \left(1 + \frac{V_0}{V_{mp,ref}}\right)}{X} \quad (i)$ $P_{str2} = P_{str,ref} (1 - c_1 S^2 - c_2 S) \quad (ii)$ $P_{str3} = P_{str,ref} [c_3 (S - 1) + G_{norm}] \quad (iii)$ $P_{str} = \text{Maximum}(P_{str1}, P_{str2}, P_{str3})$
21.	$P_{PV} = \left(\frac{G_T}{G_{ref}}\right) \times df \times [P_{ref} + \mu_P (T_{PV} - T_{ref})]$

Table 2.2. Various equations for estimating cell temperature of a solar PV module [35]. Sources and variables are stated within the reference.

Sr. No.	Model	Remarks
1.	$T_{PV} = 1.14(T_a - T_{ref}) + 0.0175 \times (G_T - 300) + 30$	Based on environmental parameters
2.	$T_{PV} = 1.14(T_a - T_{ref}) + 0.0175 \times (G_T - 300) + 30 - cf \times v$	Based on environmental parameters
3.	$T_{PV} = T_a + \frac{0.32}{8.51 + 2.1 \times v} G_T$	Skoplaki model; For free stream wind velocity ($v > 0$) m/s.
4.	$T_{PV} = T_a + \frac{0.25}{5.7 + 3.8 \times v} G_T$	Skoplaki model; v is the wind velocity component parallel to the surface of PV array.
5.	$T_{PV} = \frac{T_a + (\alpha_{PV} - \eta_{PV})G_T + (c_1 + c_2 T_a)}{(17.8 + 2.1 \times v)}$	Schott model; Based on environmental and optical parameters.
6.	$T_{PV} = T_a + c_1 G_T (1 + c_2 T_a) (1 - c_3 v) (1 - 1.053 \times \eta_{PV})$	Servant model; c_1 , c_2 and c_3 are empirical constants; includes cell efficiency.
7.	$T_{PV} = 0.943T_a + 0.028G_T - 1.528v + 4.3$	Based on environmental parameters.
8.	$T_{PV} = T_a + k_r \times G_T$	Ross model; Estimate instantaneous value; k_r depends on the module specifications and environmental conditions; $k_r = 0.02 - 0.054$.
9.	$T_{PV} = \frac{(\alpha_{ref} - \eta_{PV,ref})G_T + T_a[h_{ref} + 2.0v(1 + \cos \beta)]T_{sky}T_a^2 + h_{cb} + 4\sigma T_a^2 F_s F_b}{h_{ref} + 2.0v(1 + \cos \beta) + h_{cb} + 4\sigma T_a^2 F_s F_b}$	Ingersoll model; Predicts the average steady-state cell temperature; Includes environmental, geometrical, optical, and thermal properties.
10.	$T_{PV} = T_a + \left(\frac{\alpha - \eta_{PV}}{U_{int}}\right) G_T$	Based on energy balance
11.	$T_{PV} = T_a + (219 - 832 \times k_i) \frac{(T_{NOCT} - 20)}{800}$	Modified NOCT model
12.	$T_{PV} = \frac{U_{int} T_a + G_T(\alpha_{ref} - \eta_{ref})(1 + \rho_s T_{ref})}{U_{int} - \rho_s \eta_{ref} G_T}$	Mattei et al. model; Based on energy balance.
13.	$T_{PV} = T_a + \frac{G_T}{c_{ref}} [0.0712v^2 - 2.411v + 32.96]$	Based on environmental parameters.
14.	$T_{PV} = \frac{4[pf \times \alpha_{PV} + \alpha_{ref}(1 - pf)]G_T + (U_{int,front} + U_{int,rad})T_a}{U_{int,front} + U_{int,rad}}$	Based on energy balance
15.	$T_{PV} = T_a + \left(\frac{9.5}{5.7 + 3.8 \times v}\right) \frac{G_T}{G_{NOCT}} (T_{NOCT} - T_{a,NOCT}) \left(1 - \frac{\eta_{PV}}{\eta_{ref}}\right)$	Includes wind speed parameter in Ref [50]
16.	$T_{PV} = T_a + G_T \left[e^{(c_1 + c_2 v)} + \frac{(T_{PV} - T_{back})r_{ref}}{U_{ref}} \right]$	King et al. model; Dimensionally inconsistent.
17.	$T_{PV} = T_a + 0.031G_T - 0.058$	Based on Ross model
18.	$T_{PV} = T_{st} + k \eta_{th} G_T$ where, $k = \frac{1 - F_k}{F_g U_{int}}$	Includes energy balance in Ross model.
19.	$T_{PV} = T_a + \frac{G_T}{c_1 + c_2 v} \left[(1 - \rho)(1 - \eta_{PV}) - \sigma \frac{T_{PV}^4 - T_{sky}^4}{G_T} \right]$	Based on environmental and optical parameters; Includes sky temperature.
20.	$T_{PV} = T_a + G_T \left(\frac{\alpha}{U_{int}} \right) \left(1 - \frac{\eta_{PV}}{\eta_{ref}} \right)$	Included transmittance in Ref. [160]
21.	$T_{PV} = 3.12 + 0.025G_T + 0.899T_a - 1.3v$	Based on environmental parameters.
22.	$T_{PV} = T_a + \frac{G_T}{G_{NOCT}} \left(\frac{U_{int,NOCT}}{U_{int}} \right) (T_{NOCT} - T_{a,NOCT}) \left(1 - \frac{\eta_{PV}}{\eta_{ref}} \right)$	Suitable for free standing PV array; Not suitable for BIPV.
23.	$T_{PV} = \frac{(U_{int}/pf) - (m/pf)(T_a + T_{PV})}{2(m/pf)} \left[(1 + Y)^{1/2} - 1 \right]$ $Y = \frac{4(m/pf) \left[(U_{tot}/pf)T_a + (\alpha - \eta_{PV,ref})G_T \right]}{(U_{tot}/pf) - (m/pf)(T_a + T_{PV})^2}$ $\eta'_{PV,ref} = \eta_{PV,ref} \left[1 + X_1 T_{PV,ref} + X_2 \ln \frac{G_T}{G_{ref}} \right]$	Based on environmental parameters and heat loss by radiation.
24.	$T_{PV} = 30 + 0.0175(G_T - 150) + 1.14(T_a - 25)$	Based on incident radiation and ambient temperature
25.	$T_{PV} = T_a + c_1 G_T (1 + c_2 T_a) (1 - c_3 v)$	Servant model; Based on environmental and optical parameters.
26.	$T_{PV} = \frac{T_a + [\alpha - \eta_{PV}(1 + \rho_s T_{ref})] \left(\frac{G_T}{U_{int}} \right)}{1 - \eta_{PV} \rho_s \left(\frac{G_T}{U_{int}} \right)}$	Based on environmental, geometrical and optical parameters.
27.	$T_{PV} = T_a + 0.028G_T - 1$	Based on Ross model
28.	$T_{PV} = T_a + \frac{G_T}{U_{ref}} \left[T_{max} e^{(cf \times v)} + T_{min} + (T_{PV} - T_{back})r_{ref} \right]$	King model
29.	$T_{PV} = 30.006 + 0.0175(G_T - 300) + 1.14(T_a - 25)$	Based on environmental parameters.
30.	$T_{PV} = T_a + \frac{G_T}{G_{NOCT}} (T_{NOCT} - T_{a,NOCT}) \left(1 - \frac{\eta_{PV}}{\eta_{ref}} \right)$	Davies et al. model; Assumes constant heat transfer coefficient.
31.	$T_{PV} = T_a + G_T \left(\frac{\alpha}{U_{int}} \right) \left(1 - \frac{\eta_{PV}}{\eta_{ref}} \right)$	Based on steady state energy balance.
32.	$T_{PV} = T_a + \frac{G_T}{800} (T_{NOCT} - 20)$	NOCT model
33.	$T_{PV} = T_a + 0.0155G_T + 0.7$	Based on Ross model
34.	$T_{PV} = \frac{4(\alpha \times pf) + \alpha_{ref}(1 - pf)G_T - (\eta_{PV} \times G_T \times pf) + U_{int,front} T_a + U_{int,rad} T_{ref}}{U_{int,front} + U_{int,rad}}$	Based on energy balance equation of solar cell and tedlar
35.	$T_{PV} = T_a + 0.031G_T$	Based on Ross model
36.	$T_{PV} = 3.81 + 0.0282G_T + 1.31T_a - 1.65v$	Based on environmental parameters.
37.	$T_{PV} = T_a + \frac{G_T}{800} (T_{NOCT} - 20) + c(v - 1)$	Based on NOCT model; Includes the impact of wind speed.

Table 2.3. Various equations for estimating efficiency of solar PV module [35]. Sources and variables are stated within the reference.

Sr. No.	Model
1.	$\eta_{PV} = \eta_{ref} [1 - \mu_{\eta} (T_{PV} - T_{ref}) + \omega \text{Log}_{10}(G_T)]$
2.	$\eta_{PV} = \eta_{ref} - 22.4 (T_{PV}^{1/4} - 273^{1/4})$
3.	$\eta_{PV} = \eta_{ref} \left[1 - \mu_{\eta} (T_a - T_{ref}) - \frac{\mu_{\eta} \tau \alpha G_T}{U_{tot}} \right]$

Table 2.4. Various equations for simulating battery state of charge [35]. Sources and variables are stated within the reference.

Sr. No.	Model
1.	$SOC(t+1) = SOC(t) + \frac{\eta_{bat}(t) I_{bat}(t) \Delta t}{W(t)}$
2.	$SOC = SOC_0 + \frac{1}{W_{norm}} \int_{t_0}^t (I_{bat} - I_L) dt$
3.	$SOC = SOC_0 [1 - \frac{\kappa}{24}(t - t_0)] + \int_{t_0}^t \left(\frac{I_{bat} \eta_{bat}}{W} \right) dt$
4.	$SOC_t = \left[SOC_{t-1} (1 - \kappa) + \eta_{ch} \left(\frac{E_{ex}}{\eta_{inv}} \right) \right]$
5.	$SOC_t = \left[SOC_{t-1} (1 - \kappa) - \left(\frac{E_{def}}{\eta_{inv} \times \eta_{dis}} \right) \right]$

2.5 Simulating Residential Load Profiles

To understand the effect of multiple interconnected SAPV systems, different residential load profiles will have to be generated for each SAPV system. However, residential load profiles differ greatly depending on the 'occupant'. For example, office workers, retirees, early birds, night owls, singles, families, rich, and poor will all have different expected load profiles. Considering that measured profiles are not easily available, and that the use of average profiles often yield misleading results [36], simulating load profiles is likely the only available option. For this purpose, various techniques for modeling residential sector energy consumption will be analyzed.

Two fundamentally different approaches for simulating residential load profiles are "Top-Down" and "Bottom-Up", referring to the hierarchical level of the data inputs.

2.5.1 Top-Down Approach

Top-down methodologies consider the situation as a whole (considering national energy statistics for instance) and try to attribute an electricity consumption to the studied household stock with regard to its characteristics without distinguishing the effect of individual end-uses [37]. Variables which are commonly used by top-down models include macroeconomic indicators (gross domestic product, employment rates, price indices), climatic conditions, housing rates, and estimates of appliance ownership and number of units in the residential sector [38].

2.5.2 Bottom-Up Approach

The bottom-up approach was developed to identify the contribution of each end-use towards the aggregate energy consumption value of the residential stock [38]. Models can account for the energy consumption of individual end-uses, individual houses, or groups of houses and these results can be extrapolated to represent the region or nation based on the representative weight of the modeled sample [38]. Com-

mon inputs to bottom-up models include geometrical and thermal properties of the dwelling areas, equipment and appliances consumption history and technical properties, weather information, historical electrical consumption of the dwelling, and expected human behavior [37].

This thesis does not require an in-depth knowledge of end uses, historical data is available, and bottom-up approach is not as easily adapted. Therefore, the bottom-up approach is not appropriate for this research.

2.6 Optimum Sizing of SAPV Systems

The purpose of this section is to describe the importance of careful sizing in SAPV systems, propose technical and economic evaluation criteria for designing SAPV systems, and introduce several methods (intuitive, numerical, analytical, commercial software, intelligent, and hybrid) for sizing SAPV systems. The technical and economic criteria and sizing method chosen for this thesis and why will be discussed further in the Methodology section.

Because there is no steady backup power supply, the sizing of an SAPV is a crucial part of the system design [39]. Sized correctly, the combination of renewable energy sources with energy storage satisfies power output fluctuations with a certain reliability of supply specified by the user at minimum capital and operational costs.

2.6.1 Evaluation Criteria

The first step in sizing an SAPV system is choosing appropriate evaluation criterion. Various parameters (technical, economic, social and political) can be taken into consideration in designing an SAPV system as shown in Figure 2.3. Social and political parameters are outside the scope of this research. Some popular evaluation criteria are shown in Table 2.5.

Table 2.5. Some popular evaluation criteria for sizing SAPV systems [35]. Sources and variables are stated within the reference. 'Table 4' in this table refers to Table 2.4 in this thesis.

Definition	Mathematical formulae
<i>Objective functions</i>	
To minimize the NPC.	$NPC = \sum_{t=0}^t \frac{C_0 + C_{OM} + C_F}{(1+r)^t}$
To maximize the NPV	$NPV = -C_0 + (C_B - C_{OM} - C_F) \left[\frac{(1+r)^t - 1}{r(1+r)^t} \right]$
To minimize the LUCE.	$LUCE = \sum_{t=0}^t \frac{(C_0 + C_{OM} + C_F)/(1+r)^t}{E_t/(1+r)^t}$
To minimize the simple payback period.	$SPP = \frac{C_0}{C_B - C_{OM} - C_F}$
To minimize the discounted payback period.	$DPP = \frac{\ln(C_B - C_{OM} - C_F) - \ln\{(C_B - C_{OM} - C_F) - rC_0\}}{\ln(1+r)}$
<i>Constraints</i>	
Loss of load probability	$LLP = \frac{t_{load,def}}{t_{load}}$
Capacity shortage	$CS = \frac{E_{def}}{E_{load}}$
Excess electricity	$E_{ex} = E_{PV} - E_{load}$
Battery state of charge	$SOC_t = \frac{W_t}{W}; \text{ (Table 4)}$

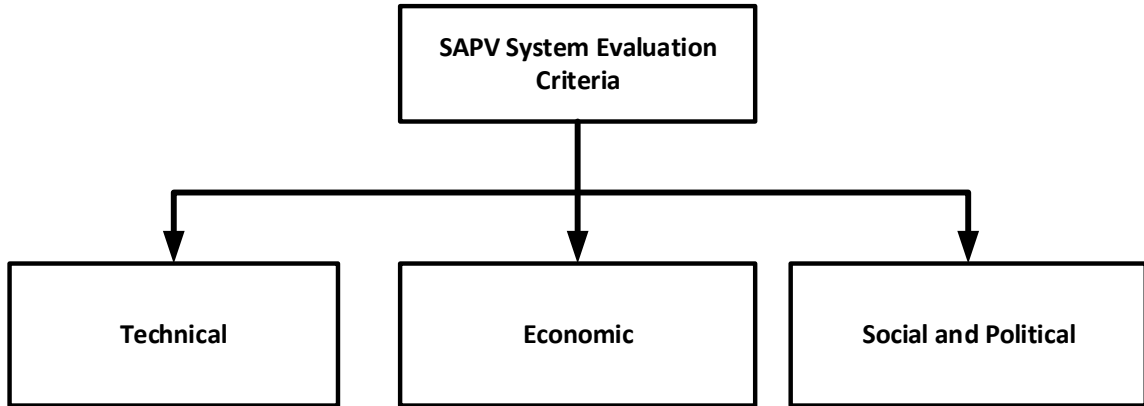


Figure 2.3. Evaluation Criteria for SAPV sizing optimization

Technical Considerations

Technical considerations are due to the fact that solar radiation is not uniform and the power must be supplied reliably. Some parameters to consider are:

- **Loss of Power Supply Probability (LPSP)**- The percentage of power supply that is not able to satisfy the load demand. Used to indicate the reliability of a power supply [40].
- **Loss of Load Probability (LLP)**- Indicates how often a system is not being able to satisfy the load demand or the mean load percentage not met by the system [41].
- **Loss of Load Expected (LOLE)**- The amount of energy not provided to load demand when the load demand exceeds the energy generation from the system.
- **Equivalent Loss Factor (ELF)**- The ratio of effective time period in hours of load outage to the total operation time in hours.
- **Total Energy Loss (TEL)**- The energy loss due to the extra power generated from a standalone energy system.

- **State of Charge (SOC)**- The amount of energy that can be stored in a system for the purpose of selecting a suitable battery capacity for a given system.
- **Level of Autonomy (LA)**- The time ratio expressed as the percentage of load covered based on the operational time of the system.
- **% PV Generation Utilization**- The ratio of utilized PV generation to total PV generation [10].

(References indicated give the definition, equation, and provide an example of using the technical consideration in sizing an SAPV.)

Economic Considerations

The general concept of optimum design is to design an SAPV system that can meet the load demand at a defined level of security, and at minimum capital and operational costs [21]. Thus, the following economic parameters can be considered:

- **Capital Cost**- The initial investment without considering operation or maintenance costs.
- **Net Present Cost (NPC)**- The present value of all initial investment, operation and maintenance cost and financial cost.
- **Net Present Value (NPV)**- Calculated by adding the present value of all incomes and subtracting the NPC during the life of an SAPV system. A positive value indicates that the SAPV system is a benefit.
- **Simple Payback Period (SPP)**- A simple financial tool which does not consider time value of money but simply calculates the time period needed to recover the invested money.
- **Annualized Cost of a System (ACS)**- The summation of annualized capital system cost, annualized operational and maintenance costs, and the annualized replacement cost [40].

- **Total Life Cycle Cost (TLCC)**- Defined as the summation of the net present values of all the amount of the system costs such as the capital cost, maintenance and operation costs, replacement costs, etc. [42].
- **Capital Recovery Factor (CRF)**- The ratio of the amount of constant annuity costs to the total present value of all the costs received for a given time in years [43].
- **Levelized Cost of Energy (LCE)**- Defined as the ratio of the total annual cost of the system components to the total annual energy generated by a standalone PV system [44].

(References indicated give the definition, equation, and provide an example of using the economic consideration in sizing an SAPV.)

2.6.2 Sizing Methods

”In general, in determining optimal sizing of a PV system, a specific area for a standalone PV system is first defined, and then meteorological data such as solar radiation and ambient temperature are obtained. Capacity of PV system components such as PV array, storage battery and inverter size are then calculated. It is noted that several considerations need to be taken into account in a standalone PV system sizing, such as the kWh/yr needed to cover the load demand, the kWh/yr generated by the PV system, the Ah of battery banks, the area that the system will occupy, and the system cost.” [21] Available sizing methodologies for the PV array size and the storage battery capacity (intuitive, numerical, analytical, commercial software, intelligent, and hybrid) are given in Figure 2.4. The sizing method chosen, numerical methods, will be discussed in more detail in the Methodology section (Chapter 3).

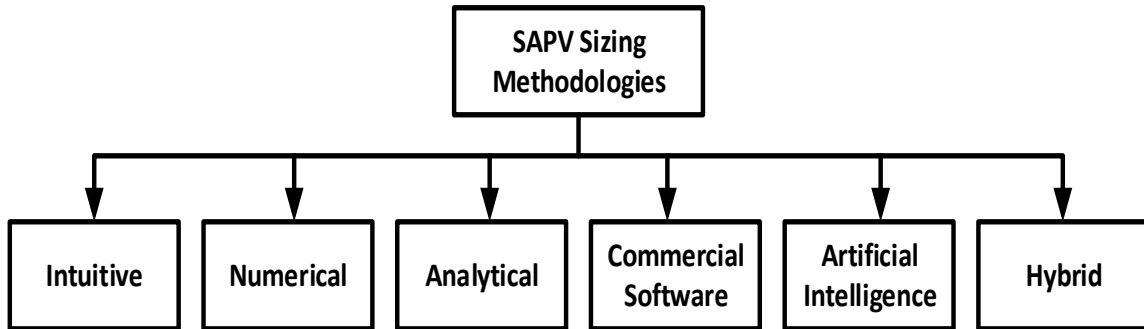


Figure 2.4. Sizing methodologies for SAPV systems

Intuitive

A simplified calculation of the size of the system is carried out without establishing any relationship between the different subsystems nor taking into account the random nature of solar radiation [45]. A common intuitive approach is the "worst month method" where the energy input required is taken to be the month with the worst conditions for the system. The calculation is greatly simplified but this usually results in over-sizing the installation, and prevents any kind of energy or economic optimization. As a result, this method is only suitable to be used for estimating initial and rough approximation of the standalone PV system [21].

Numerical

In numerical methods, simulations are carried out at each time interval, usually an hourly or daily time period in either a deterministic or stochastic approach. Stochastic considers the effect of solar radiation variability while deterministic does not [21]. Deterministic is useful when there are difficulties finding a data set of geological information. The stochastic approach is considered to be more accurate and allows for a quantitative analysis of the energy reliability. A stochastic numerical approach will be used for the research's model.

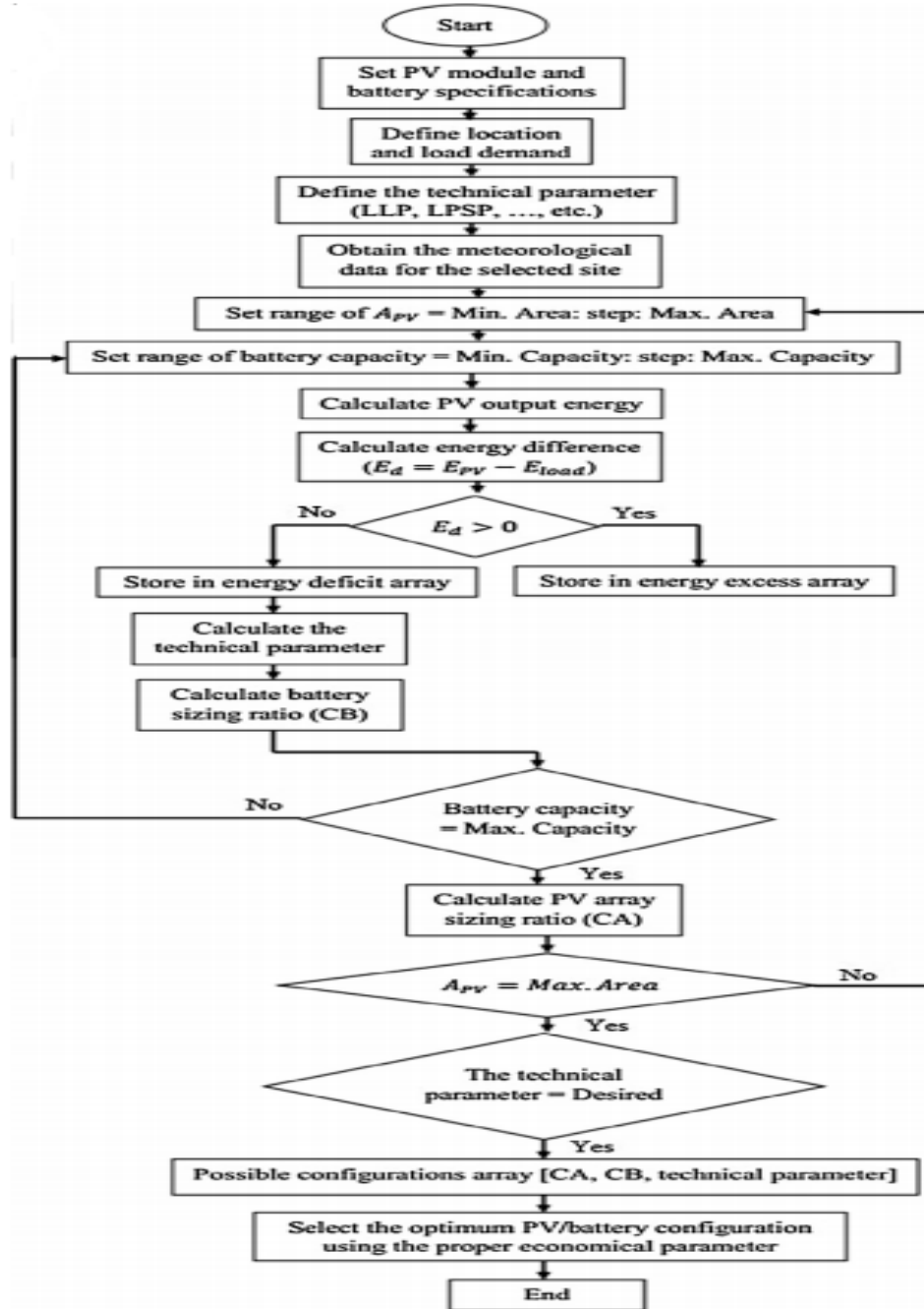


Figure 2.5. Generic numerical method flowchart [21]

A sample procedure for a numerical method is depicted in Figure 2.5. This flowchart will be taken into consideration for the development of the energy storage analysis.

Analytical

In analytical methods, the components of a standalone PV system are characterized by computational mathematical models as a function of reliability so as to determine a system's feasibility [21]. The advantage of the analytical method is that sizing calculations are simple while the disadvantage is the difficulty in estimating coefficients of the mathematical equations which are location dependent [46].

Commercial Software

Currently, many software tools such as Hybrid Optimization Model for Electric Renewables (HOMER), Improved Hybrid Optimization by Genetic Algorithms (HOGA), Transient Systems Simulation Program (TRNSYS), RETScreen, and PV.MY are available for optimal sizing of an SAPV, none of which facilitate energy sharing strategies between SAPV systems.

Intelligent

Artificial intelligence (AI) methods are used to overcome the unavailability of meteorological data for sizing a standalone PV system in remote areas [21]. Because meteorological data is widely available across the US, AI methods will not be an appropriate sizing method for the proposed energy infrastructure.

Hybrid

Hybrid methods combine two or more different methods to obtain the optimal result usually to overcome the perceived disadvantages of the previous methods. Although most optimization problems are multi-objective in nature, the hybrid method usually introduces complex algorithm functions which are not appropriate for adding functionality (energy sharing).

3. METHODOLOGY

This chapter describes the methodology for investigating the proposed energy infrastructure in detail including the research design; inputs such as project specifications, component specifications, solar irradiation data, and residential load data; procedures such as simulating solar irradiation, simulating residential loads, predicting PV and ESS performance, predicting energy infrastructure performance, and optimally sizing of SAPV; outputs such as Loss of Power Supply Probability, and Capital Cost; explanation of the code through flowcharts and variable descriptions; validation methods; analysis methods; and summary.

3.1 Research Design

The research goal is to solve the problem statement: "What type of SAPV energy sharing strategy has the lowest total cost? For each sharing strategy, how does initial charge, load variation, number of SAPV systems, geographic location, required reliability, and starting month affect total cost and energy storage required?"

The variables initial charge, geographic location, required reliability, and starting month were chosen as a natural progression from the software development. Looking at isolated SAPV systems it made sense that the same variables would be important in interconnected systems. Load variation was investigated because this is what makes energy trading worthwhile. If every system has the same load and PV generation than there will not be any instances where it is beneficial for them to trade. Finally, the number of SAPV systems was chosen because it was thought that with more systems more trades would occur and the benefit of establishing a transactive microgrid would increase. Component specifications (PV rating, PV cost, battery efficiency, battery cost) could have been investigated to show how these specifications must be improved

to make transactive microgrids economical, but it made sense to start with current technologies.

To determine the effect of initial charge, one hundred trials will be conducted for six cases (1%, 5%, 10%, 15%, 20%, and 100% initial charge) for the months of March, July and November, keeping the number of SAPV systems (five), geographic location (Indianapolis), and required reliability (nine hours a year or 0.1% LPSP) constant. Values were chosen to get a complete picture of the typical range (5% to 20%) and an outlier on each end (1% and 100%). One hundred trials was chosen for all of the simulations because initial simulations showed that the values converge without taking a very large time. Ten trials gave values that did not converge and one thousand trials took more than thirty minutes per simulation. The purpose of investigating the effect of initial charge is to find a reasonable baseline and to explore the effect of initial charge. The hypothesis is that initial charge will not have much of an effect for the values between 5% and 20% but that it will have more of an effect for low initial charge if the initial month is in the winter because the simulation will begin when there is less PV generation.

To determine the effect of the starting month (day 1 of simulation) 100 trials will be conducted for each month (12 cases), keeping the initial charge (10%), number of SAPV systems (5), geographic location (Indianapolis), and required reliability (9 hours a year or 0.1% LPSP) constant. Every month was considered to get a complete picture of the effect. The results for varying starting month will be used to determine a baseline starting month for the rest of the simulations. The hypothesis is that the selection of any month besides a winter month will give typical results.

To determine the effect of load variation 100 trials will be conducted for 2 cases: all systems having the same load and all systems having loads simulated using the load simulator, keeping the initial charge (10%), number of SAPV systems (5), geographic location (Indianapolis), required reliability (9 hours a year or 0.1% LPSP), and starting month (June) constant. The purpose of this test is to demonstrate the justification of load simulation. The hypothesis is that if every system is considered to

have the 'typical residential load profile' then there will be no benefit in establishing energy infrastructure, but this is not indicative of real life load profiles where people have different time schedules.

To determine the effect of the number of SAPV systems, geographic location, and required reliability 100 initial trials of the following cases will be conducted:

- Number of Systems = (2, 5, 10, 20, 50)
- Geographic Location = (Phoenix, Arizona; Little Rock, Arkansas; Indianapolis, Indiana; Erie, Pennsylvania)
- Required Reliability = (0.1%, , 0.2%, 0.5%, 1% LPSP)

The number of systems were chosen so that a wide range of number of systems could be investigated. In the model, increasing the number of systems greatly increases the computation time. The case of 100 systems was not investigated because the computation took more than an hour per simulation.

The reasons these specific locations were chosen are that they all have Class 1 (low uncertainty) data from TMY3, they represent a spectrum of different yearly average Global Horizontal Irradiance (GHI) values, and they provide examples from each climate zone in the US. Another reason for including geographic location, besides investigating different climate zones, is to verify that the effect of number of SAPV systems and required reliability applies for various datasets.

The values for required reliability were chosen to show the typical range that residential customers would accept. Nine hours is the standard for utilities across the U.S. and ninety hours would be considered a large amount of outage for a typical residential customer.

Five possible number of systems, four geographic locations, and four required reliability options gives a total of eighty cases (eight thousand trials). Constant variables include starting month (June), initial charge (10%), and component specifications. The hypothesis is that the number of systems and required reliability will have a large

effect on the total cost of the IES and CES cases in comparison to the Baseline case, this effect will be seen in each geographic location, and the geographic location will affect the total cost but not in comparison to the Baseline case.

3.2 Model Development

The research is carried out through the 'main' file "Main.m" which is outlined below and through the flowchart in Figure 3.1. Functions called by "Main.m" which can be better explained by flowchart including "Solar_Cumulative_STM_Generator.m", "Solar_Irradiation_Simulator.m", "Baseline_Analysis.m", and "IES_Analysis.m" can be found in Figures 3.2, 3.3, 3.4, and 3.5 respectively.

1. **Main.m** - The main project file given in Figure 3.1. Input the excel file name, number of SAPV systems, number of trials, number of acceptable outage hours, number of years of simulation, geographic location of solar and load data, initial charge of battery, and starting month and then follow the flowchart through each function until finally a table is output for the baseline, CES, and IES cases.
2. **TMY3_Input.m** - Input geographic location by changing the filename of solar and load data to fill the variables "Solar_Data" and "Load_Data". These outputs will be used to generate synthetic solar and load data.
3. **Component_Specifications.m** - Input component specifications such as Solar Panel Rating, Solar Panel Unit Cost, Solar Panel Installation Cost, Range of Solar Panels to test, PV De-rating Factor, Battery Capacity, Battery Efficiency, Battery Unit Cost, Battery Hardware Cost, Battery Installation Cost, and Initial Battery. These inputs will be described in more detail in the next section "Inputs".
4. **Solar_Cumulative_STM_Generator.m** - Generates a cumulative STM based on the provided solar data. The outputs include "Maximum_Solar" which gives the largest value of solar irradiation rounded to the nearest ten, and

"Big_Cumulative_Solar" which is the cumulative STM which will be used to simulate solar. Given by Figure 3.2.

5. **Solar_Irradiation_Simulator.m** - Takes "Maximum_Solar" and "Big_Cumulative_Solar" and generates solar irradiation data for each trial. Each system is considered to receive the same amount of solar irradiation. The output is a matrix of all simulated solar data for each trial "Simulated_Solar" which will be used to calculate the PV output from each system. Given by Figure 3.3.
6. **PV_Output_Calculator.m** - Calculates the PV output energy for each possible PV configuration based on "Simulated_Solar." The outputs are "Total_PV_Generation" which will be used to calculate % PV Utilization, and "PV_Output" which will be used in energy storage analysis. Refer to Equation 3.1 for how the PV output is calculated from PV derating factor and simulated solar data.
7. **Load_Demand_Simulator.m** - Takes "Load_Data" and simulates for each SAPV system a random offset from the typical residential load profile. The load can be offset between 2 hours ahead and 2 hours behind and will start between 2 days ahead or 2 days behind. This introduces variability by giving a total of 25 possible different load profiles for each trial. The outputs are "Hourly_Load" which stores the hourly load for all systems and "Shared_Hourly_Load" which is the sum of the load of all systems for each trial. No flowchart is given for this function because it simply shifts the load.
8. **Baseline_ESS_Analysis.m** - Given by Figure 3.4. Performs an energy storage analysis based on "Hourly_Load" and "PV_Output." Battery State of Charge (SOC) begins at the specified initial charge and is calculated every hour. If battery SOC exceeds 100% that energy is stored in energy excess array "LOPVG_loss" and "LOPVG_Count" is incremented. If battery SOC equals 0% the amount of energy not supplied is stored in an energy deficit array "LOS_lack" and "LOS_Count" is incremented. If the reliability requirement is not met

(LOS_Count \leq LPSP) then the battery is incremented and analysis is repeated. Once the reliability requirement is met, a table is output which gives all useful information from the analysis including number of batteries required, LOPVG count and loss, % PV Utilization, and capital cost. This is repeated for the number of systems, number of configurations, and for the number of trials. At the end, a table is output which gives the average performance of each configuration from all systems and trials. Finally, all of the tables are written to an Excel file outside of the for loops to speed up the simulation.

9. **Central_ESS_Analysis.m** - Performs the same function as "Baseline_ESS_Analysis" except based on "Shared_Hourly_Load" and "Shared_PV_Output" which is to say that all systems are treated as one, having a combined PV output and Hourly Load. The table output at the end gives the average performance of each configuration from all trials and gives some extra results including total cost both as a total and as an average per system. No flowchart is given for this function because it is very similar to the baseline analysis.
10. **IES_Analysis_N_Systems.m** - Given by Figure 3.5. Performs an energy storage analysis similar to "Baseline_ESS_Analysis" where each SAPV system has its own battery and solar panel configuration but now the systems are able to share energy. If a systems battery SOC is equal to 100%, that SAPV system will attempt to sell its energy for that hour to the SAPV system with the lowest battery SOC. If no SAPV system can take the energy without going over 100% SOC itself then the energy is stored in energy excess array "LOPVG_loss" and "LOPVG_Count" is incremented. If a systems battery SOC is equal to 0%, that SAPV system will attempt to buy energy for that hour from the SAPV system with the highest battery SOC. If no SAPV system can sell the energy without reaching 0% SOC itself then the energy not supplied is stored in an energy deficit array "LOS_lack" and "LOS_Count" is incremented. If any of the systems do not meet the reliability requirement then those systems not meeting

the reliability requirement will have their batteries incremented and the analysis is repeated. Once every system meets the reliability requirement, calculation is done for all useful information from the analysis as in "Baseline_ESS_Analysis" but also including information about which how many times each system bought and sold energy and the total number of trades. This is repeated for each configuration and for the designated number of trials. Finally, all of the tables are written to an Excel file outside of the for loops to speed up the simulation. Pivot tables are created which calculates the average results over all systems.

All inputs, procedures, and outputs will be discussed in closer detail in the following sections.

3.3 Inputs

This section describes the inputs to the model including: project specifications, component specifications, solar irradiation data, and residential load data.

3.3.1 Project Specifications

Variable names for varying inputs (project specifications) to the model include:

- **Excel_File_Name** - Destination for saving output tables. Not included in Figure 3.1 to save space.
- **Number_of_SAPV_Systems** - The number of interconnected SAPV systems in CES and IES cases.
- **Number_of_Trials** - Number of trials performed. Load and PV are re-simulated for each trial. This and other variables with 'Number' in the name are specified by # in Figure 3.1.
- **LPSP_Count** - Referred to as 'Required Reliability' in Figure 3.1. The number of acceptable outage hours.

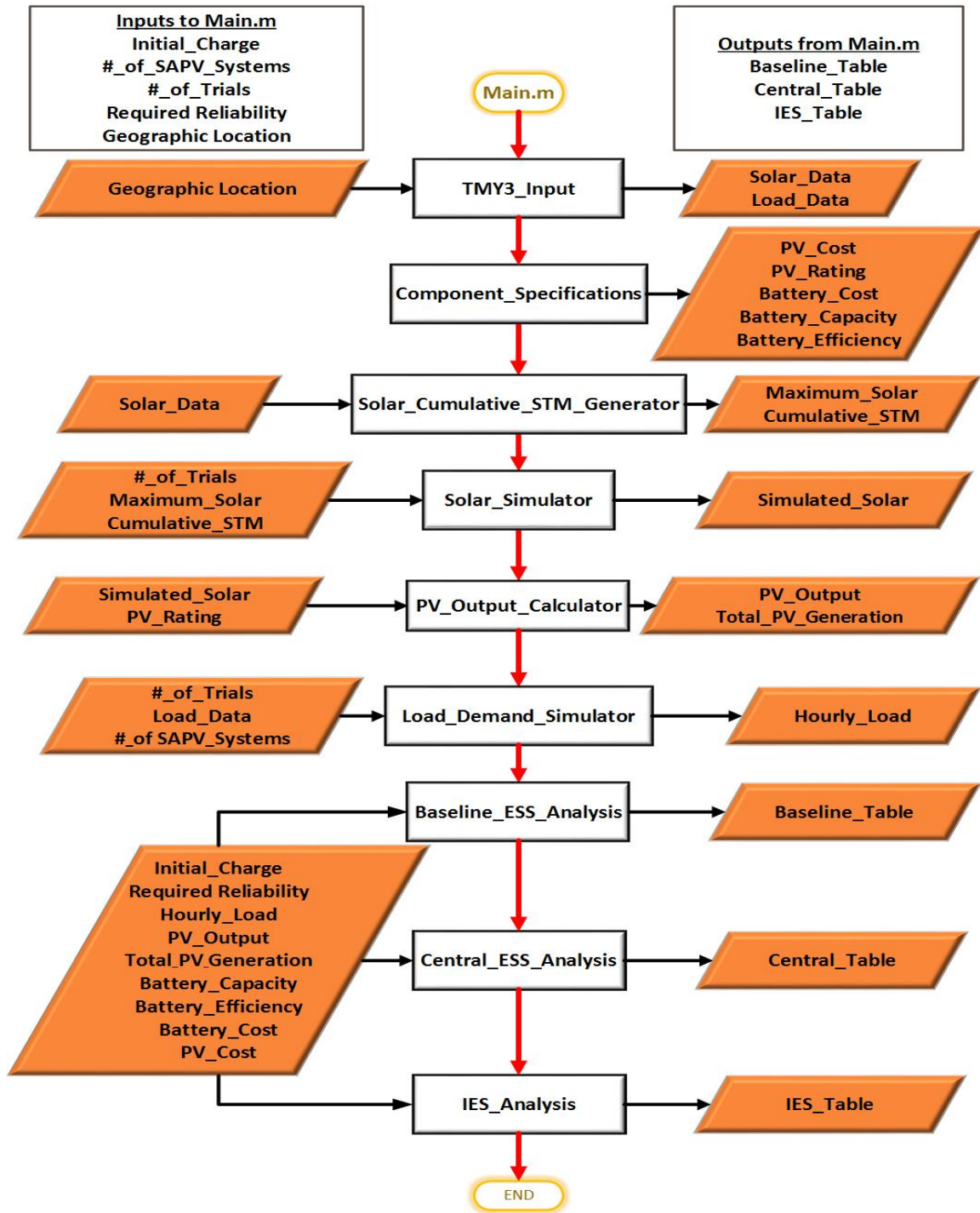


Figure 3.1. Major inputs (on the left), functions (in the middle), and major outputs (on the right) for Main.m. Final outputs are tables of results for baseline, CES, and IES.

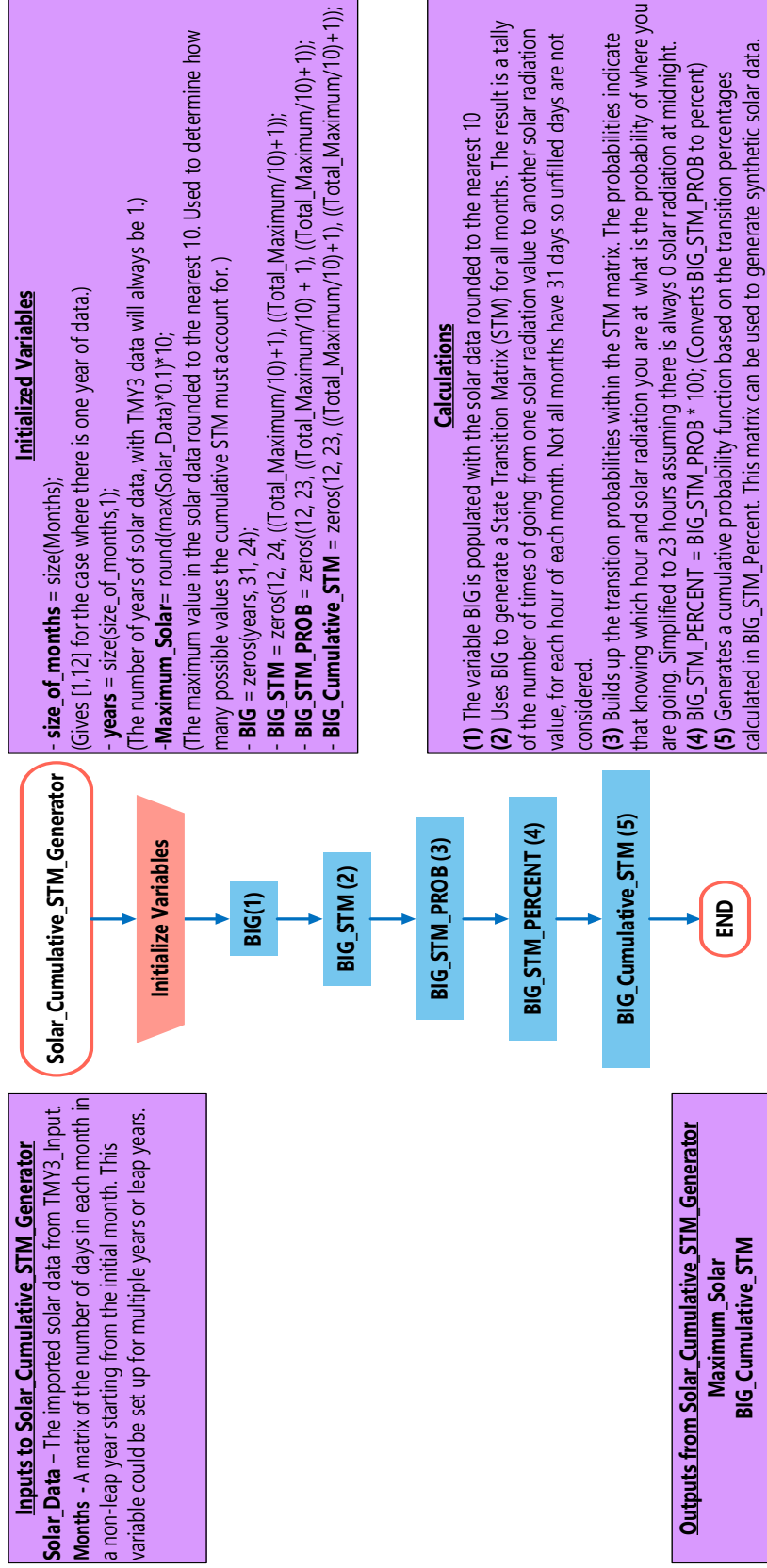


Figure 3.2. Flowchart explaining 'Solar_Cumulative_STM_Generator.m'. Outputs are Maximum_Solar and BIG_Cumulative_STM which are used to simulate solar data in Solar_Irradiation_Simulator.m (Figure 3.3).

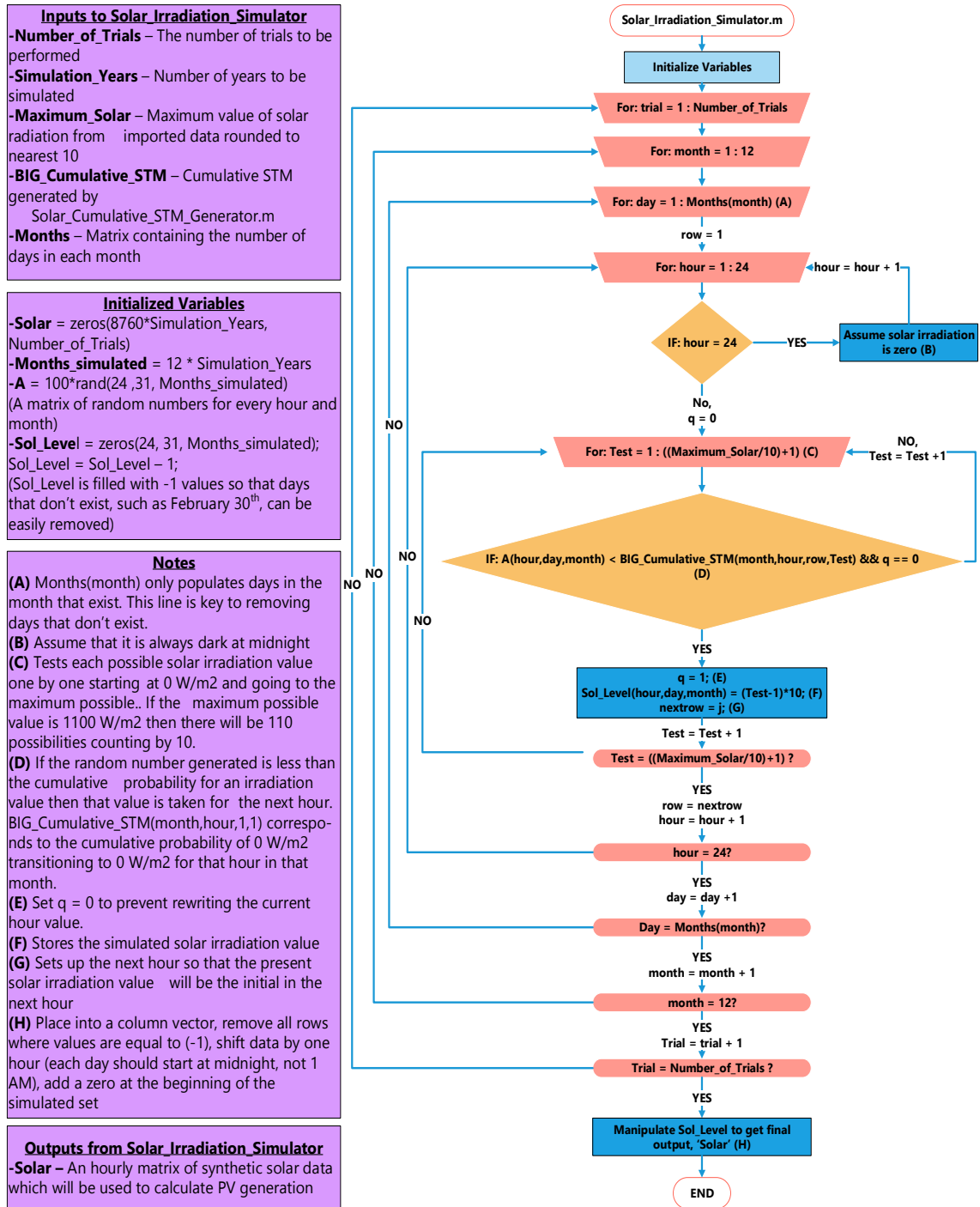


Figure 3.3. Flowchart explaining 'Solar_Irradiation_Simulator.m'. Outputs an hourly matrix of synthetic solar data which will be used by PV_Output_Calculator.m to calculate PV generation for each hour.

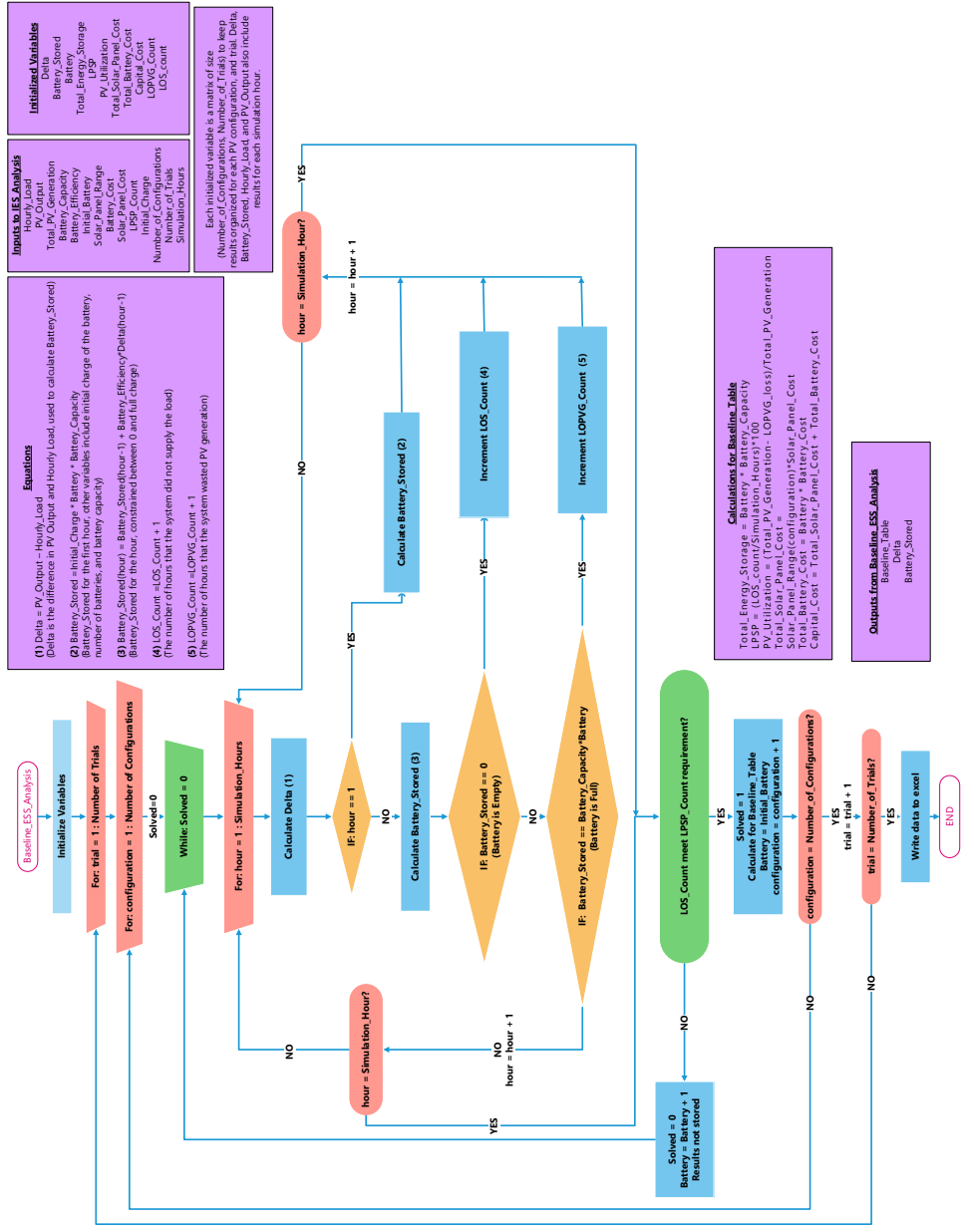


Figure 3.4. Flowchart explaining 'Baseline_ESS_Analysis.m'. 'Central_ESS_Analysis.m' works almost exactly the same way, but PV generation and hourly load are summed for each trial. Final output is a table of results with Capital Cost, Total Energy Storage, LPSP, and PV Utilization.

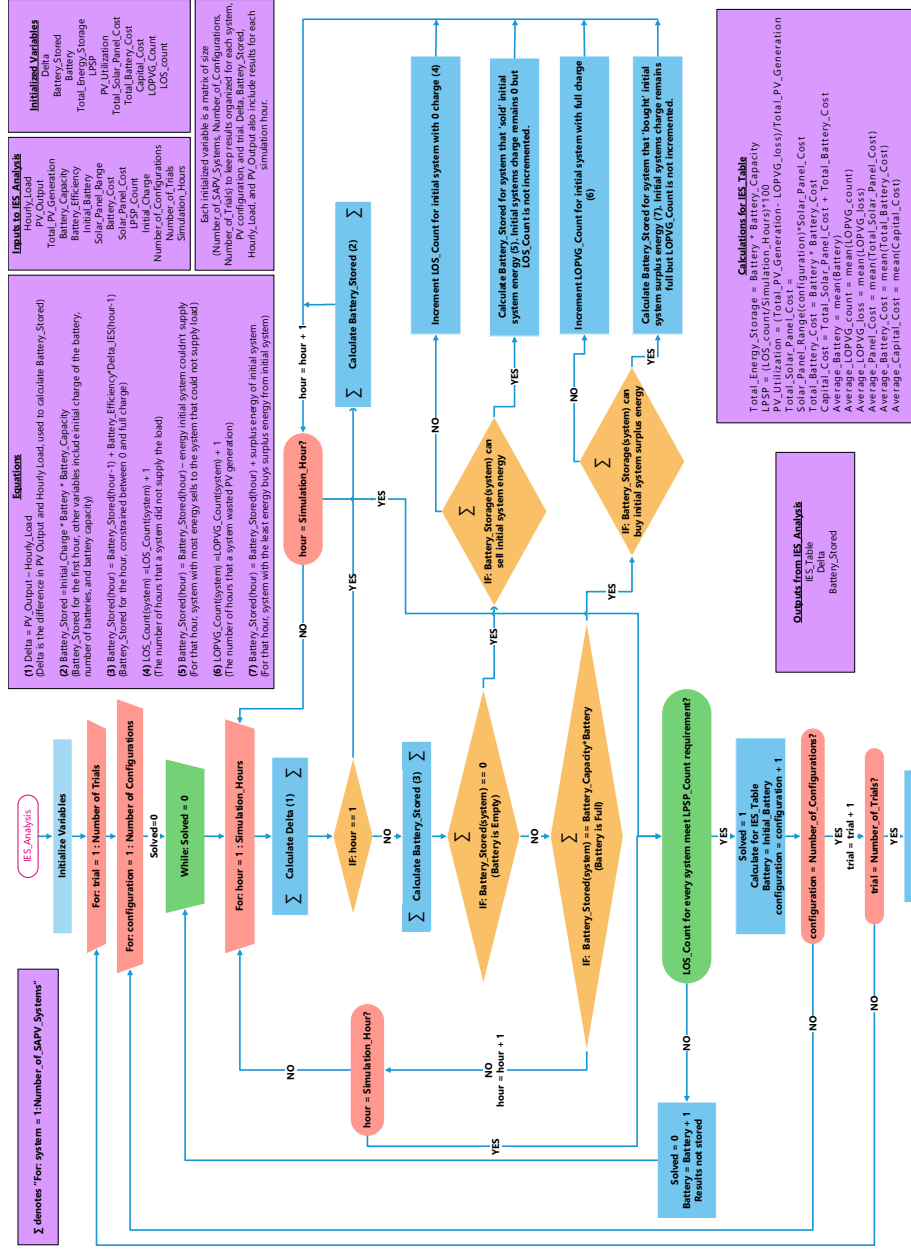


Figure 3.5. Flowchart explaining 'IES_Analysis.m'. Final output is a table of results with Capital Cost, Total Energy Storage, LSPV, PV Utilization, and Number of Trades.

- **Initial_Charge** - The initial charge of the battery system on hour 1. Given as a percentage of total battery capacity. The UN Committee of Experts on the Transport of Dangerous Goods established regulations for transporting hazardous materials. According to resolution UN 3480 no lithium battery may be transported with a SOC greater than 30%. [47] A Tesla energy advisor through phone call stated "The company does not monitor the exact SOC upon arrival, only that it is below 30% at the time it is shipped. The charge of the battery when shipped will not be equal to it's charge when it arrives mainly due to leakage losses. According to customer surveys charge upon arrival is anywhere between 5% to 20%." [48] Simulations will be conducted to determine the effect of initial charge and then the baseline will be taken as 10%.
- **Monthpoint** - Used to specify the initial hour of simulation. For instance, Monthpoint = -744 specifies that the simulation will begin on February 1st, 1 AM.
- **Simulation_years** - Whole number of years to simulate results. Only considered 1 year in this research but the model has the ability to simulate any number of years. Currently, solar data will be the same for each year but load will vary.
- **Solar_Data** - Given as a text file with 8,760 data points for every hour of a regular (non-leap) year. This variable can accept more than one year of data and consider leap years by examining commented code.
- **Load_Data** - Also given as a text file with 8,760 data points for every hour of a regular (non-leap) year. Not currently able to accept more than one year of data or leap years but can be achieved by looking at how 'Solar_Data' is handled. Figure 3.1 specifies 'Geographical Location' is used within 'TMY3_Input' to generate 'Solar_Data' and 'Load_Data' which is just to say that the file name of the source data is changed.

- **Initial_Battery** - The initial number of batteries to test. Not included in Figure 3.1 and is always one in the research. Can be used to speed up the simulation or investigate situations with more than the required number of batteries.

3.3.2 Component Specifications

Variable names for constant inputs (component specifications) including PV and ESS performance and cost parameters are described in the list below and specified in Tables 3.1 and 3.2.

PV and ESS Performance Parameters

- **Solar_Panel_Rating** - The solar panel rating in kW.
- **PV_Derating_Factor** - An empirically determined factor which considers all of the losses in A.C power generation from a solar panel including, in this case, the losses due to temperature. Not included in Figure 3.1 due to space.
- **PV_Configurations** - The range of PV configurations to test (number of solar panels). Not included in Figure 3.1 or Table 3.1 but a range of 5-20 is used because this usually covers practical values.
- **Battery_Capacity** - The 'usable battery capacity' as specified by the battery. The Tesla Powerwall has 13.5 kWh of usable capacity of which 100% can be discharged [49].
- **Battery_Efficiency** - The 'round-trip efficiency' of the battery considering charging and discharging.

Table 3.1. PV and ESS Performance Parameters

PV and ESS Performance Parameters		
Input	Value	Source
Solar_Panel_Rating	3 kW	[50]
PV_Derating_Factor	0.731	[51]
Battery_Capacity	13.5 kW	[49]
Battery_Efficiency	90%	[49]

System Cost Parameters

- **Solar_Panel_Unit_Cost** - The unit cost of the solar panel. In this case, the price is for a 3 kW solar panel kit which includes the solar panel and also an inverter and racking system. In Figure 3.1 'Solar_Panel_Cost' includes 'Solar_Panel_Unit_Cost', 'Solar_Panel_Hardware_Cost', and 'Solar_Panel_Installation_Cost.'
- **Solar_Panel_Hardware_Cost** - The cost of supporting hardware, estimated to be from \$300 to \$500 [50]. Includes wire, conduit, fittings, breakers, AC/DC Disconnects (if required), junction boxes and a sub panel (if required).
- **Solar_Panel_Installation_Cost** - Estimated by the solar panel kit source to be 1\$/W or \$3,000 per 3kW kit [50].
- **Battery_Unit_Cost** - The unit cost of the battery. In this case, the price is for a Tesla Powerwall which includes a charge controller and does not require an enclosure. In Figure 3.1 'Battery_Cost' includes 'Battery_Unit_Cost', 'Battery_Hardware_Cost', and 'Battery_Installation_Cost.'
- **Battery_Hardware_Cost** - The cost of supporting hardware, estimated by Tesla to be \$700 per Powerwall [49].
- **Battery_Installation_Cost** - \$1,000 to \$3,000 as estimated by Tesla [49]. An estimate of \$1,500 is used in the simulation.

- **Interconnection Cost** - Taken as \$200 considering that the houses are 50 foot apart, \$1/foot of wire and adding \$150 for installation. This is an especially rough estimate and needs further research.

Table 3.2. System Cost Parameters

System Cost Parameters		
Input	Value	Source
Solar_Panel_Unit_Cost	\$4,877	[50]
Solar_Panel_Hardware_Cost	\$500	[50]
Solar_Panel_Installation_Cost	\$3,000	[50]
Battery Unit Cost	\$5,900	[49]
Battery Hardware Cost	\$700	[49]
Battery Installation Cost	\$1,500	[49]
Interconnection Cost	\$200 / house	Rough estimate

3.3.3 Solar Irradiation Data

”Typical Meteorological Year (TMY) data files were first created from long-term data files in the National Solar Radiation Data Base (NSRDB) to help with the analysis of building performance at a time when computers were much slower and had smaller memory banks than today. Users wanted a one-year dataset that would emulate the results produced by using the thirty years of available data in the NSRDB. Many of the meteorological data parameters affected performance more than the incident solar radiation, and the TMY data sets were created to be typical of the meteorological data contained in the NSRDB.” [52]

TMY files were created to represent typical meteorological years and not typical solar years. Due to the limited number of years in most TMY3 data files, there is no guarantee that the TMY3 file will be an accurate representation of the average

Global Horizontal Irradiation or Direct Normal Irradiation for the entire historical data set.

Ideally, the most bankable dataset would come from a high-quality site-specific solar monitoring station that is well maintained and the measurements taken over 30 years or longer. However, very few data sets of that duration exist, and the need for short-term profitability places severe constraints on the practicality of undertaking any new and comprehensive studies before seeking funding for a project at a given site.

”A typical meteorological year (TMY) data set provides designers and other users with a reasonably sized annual data set that holds hourly meteorological values that typify conditions at a specific location over a longer period of time, such as 30 years. TMY data sets are widely used by building designers and others for modeling renewable energy conversion systems. Although not designed to provide meteorological extremes, TMY data have natural diurnal and seasonal variations and represent a year of typical climatic conditions for a location.” [52]

Understanding the limitations, the dataset chosen for solar irradiation data is Typical Meteorological Year, version 3 (TMY3), available at [53].

Figure 3.6 shows the geographical location of all TMY3 ground stations in the US. Figure 3.7 shows the climate zones used to select sites and simulate residential load data.

The 4 Locations chosen include: Erie, Pennsylvania; Indianapolis, Indiana; Little Rock, Arkansas; and Phoenix, Arizona. San Antonio, Texas was initially chosen but was dropped because it was found to have non-representative residential load values (6.5 kWh days) resulting in much larger capital cost estimates. San Antonio will however be used in the validation because it provides a useful example of how starting month and load variability could affect performance. Figure 3.8 shows the selected sites superimposed on a map of annual average daily total solar resource.

The reasons these specific locations were chosen are that they all have Class 1 (low uncertainty) data from TMY3, they represent a spectrum of different yearly

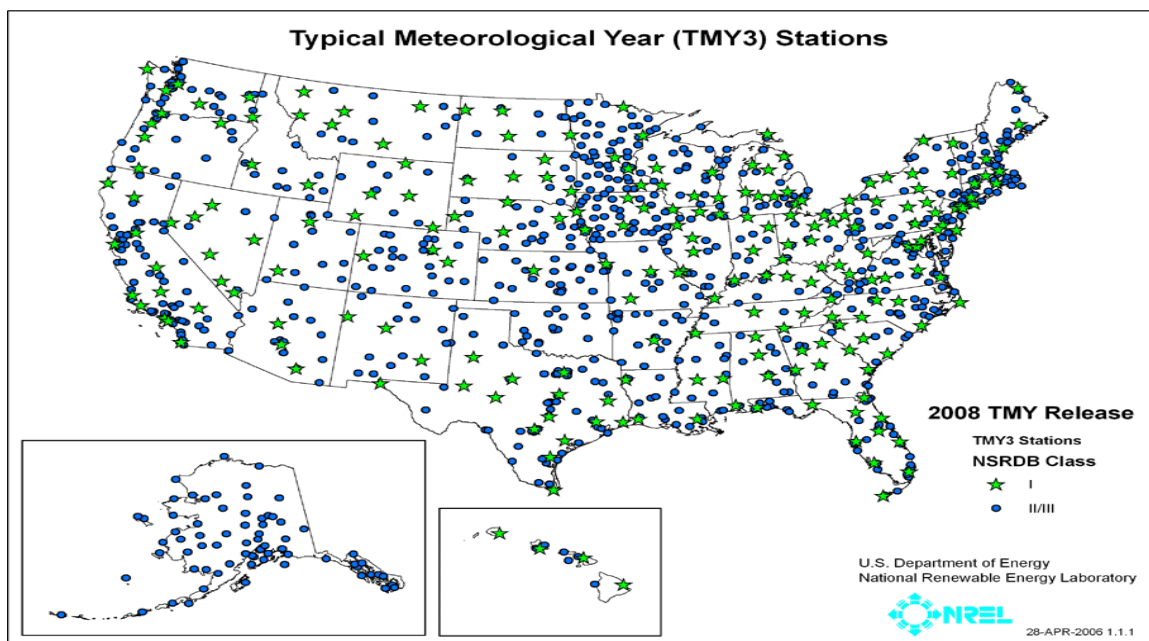


Figure 3.6. Map of TMY3 Sites: Shows the geographical location of TMY3 ground stations [52]

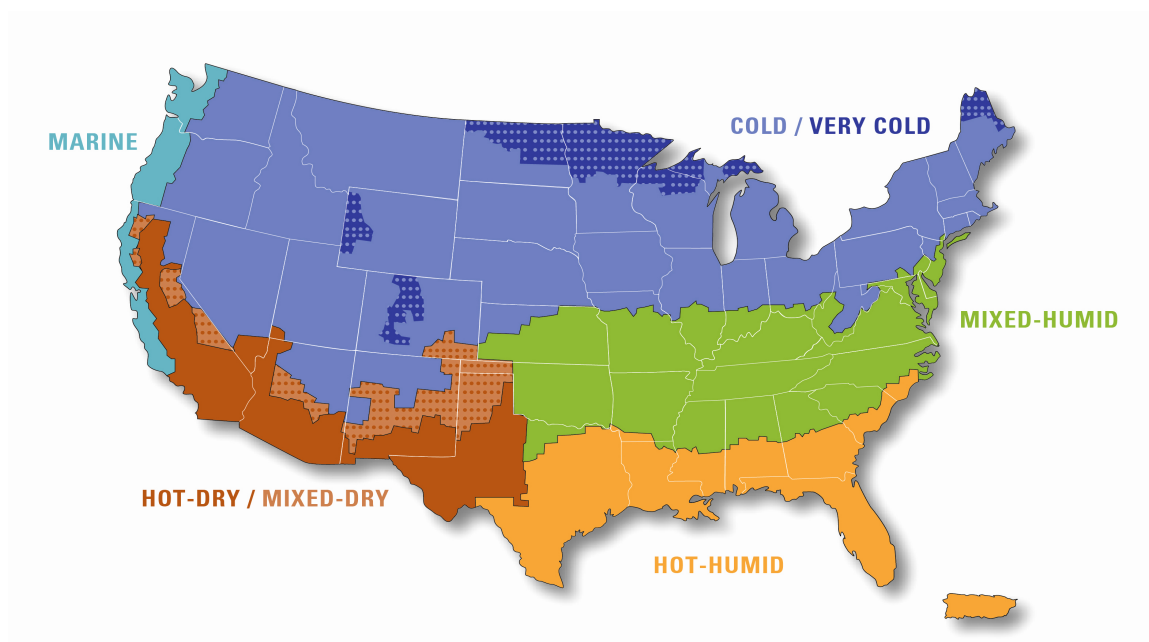


Figure 3.7. Climate map [54]

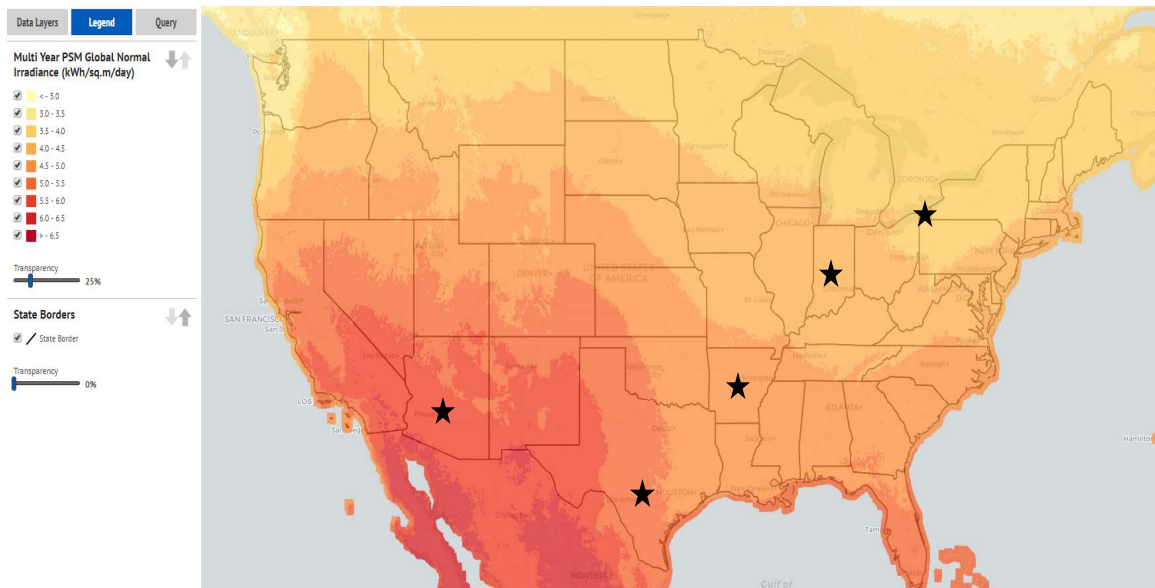


Figure 3.8. Geographical location of TMY3 ground stations chosen for this study superimposed on a map of annual average daily total solar resource from NSRDB

average GHI values, and they provide examples from several climate zones in the US. The purpose of multiple geographic locations was to show that the results are replicated among different data sets. For a complete study of transactive microgrids in every climate zone a marine climate zone should also be considered. The NSRDB Data Viewer was helpful in selecting locations because it shows monthly average and annual average daily total solar resource available [55].

3.3.4 Residential Load Data

The TMY3 residential load data was selected because it coincides with TMY3 solar data, is easily accessible and is in a favorable format. This dataset also includes typical, high and low residential hourly load profiles which will be useful for future work.

”This dataset contains hourly load profile data for 16 commercial building types (based off the DOE commercial reference building models) and residential buildings (based off the Building America House Simulation Protocols). This dataset also uses the Residential Energy Consumption Survey (RECS) for statistical references of building types by location. Hourly load profiles are available for all TMY3 locations in the United States” [56].

3.4 Procedure

3.4.1 Simulating Solar Irradiation and Residential Load

Solar irradiation data is simulated using Weissbach’s Markov model [4]. This method was chosen because it was accessible, easily understood, generates realistic results, and only requires solar irradiation data, not temperature or clearness index. As long as the results are typical and realistic, the solar irradiation simulation does not have to be super accurate for this research. Chamola’s method, although it improves Weissbach’s, is for dimensioning high-reliability systems and was not easily accessible.

Residential load is taken straight from the residential load data. Variability is introduced by adding or subtracting hours, creating the effect that residential customers are on different schedules.

Some other strategies for simulating residential load which should be included in the future include: synthetic loads with more variability, high and low use load profiles, specific end uses (TV, heating, air conditioning, stove, microwave, etc.), electric vehicle energy storage, and smart load control.

3.4.2 Predicting PV and ESS Performance

PV performance is taken from the method that HOMER uses for calculating the output of a PV array without modeling the effect of temperature [57]. This

method was chosen because it does not require temperature data and it can easily be incorporated in Matlab.

$$P_{PV} = Y_{PV} f_{PV} \left(\frac{G_T}{G_{T,STC}} \right) \quad (3.1)$$

- P_{PV} - the output of a PV array (kW)
- Y_{PV} - the rated capacity of the PV array, it's power output under standard conditions (kW)
- f_{PV} - the PV derating factor (%)
- G_T - the solar radiation incident on the PV array in the current time step (W/m^2)
- $G_{T,STC}$ - the incident radiation at standard test conditions ($1,000 W/m^2$)

Delta is the difference in PV output and load consumed by the system in that hour indicated by Equation 3.2. A positive Delta indicates that the system generated more energy than it consumed for that hour. Delta will be used to calculate energy storage at each consecutive time step.

$$Delta = P_{PV} - P_{Hourly_Load} \quad (3.2)$$

Energy storage calculations are taken from [4]. Energy storage is calculated for the initial hour using the initial charge condition in Equation 3.3 and then in consecutive time steps using the previous time steps energy storage plus the difference in energy generated and energy consumed in the previous time-step Equation 3.4. Comparing to HOMER kinetic battery model [58] some considerations which could be included are maximum charge current, maximum discharge current, capacity ratio, temperature, temperature dependence of capacity, and maximum operating temperature.

$$ESS_{stored} = Initial_Charge \times Battery_N \times Battery_{Capacity} \quad (3.3)$$

$$ESS_{stored} = ESS'_{stored} + Delta \times Battery_{eff} \quad (3.4)$$

- ESS_{stored} - The energy available in the battery in the current time step. Equation 3.3 is only used in the first hour of simulation. Constrained between full charge ($Battery_N \times Battery_{Capacity}$) and zero charge. (kWh)
- ESS'_{stored} - The energy available in the battery in the previous time step. (kWh)
- $Initial.Charge$ - The initial charge of the battery given as a percentage of full charge. (%)
- $Battery_N$ - The number of batteries being considered. (#)
- $Battery_{Capacity}$ - The 'usable battery capacity' per battery. (kWh)
- $Delta$ - The difference in energy generated and energy consumed in the previous time-step. Calculated a step ahead because of the calculation for ESS_{stored} in hour 1. (kWh)
- $Battery_{eff}$ - The 'round-trip efficiency' of the battery. The same value is currently used whether the battery is charging or discharging. (%)

This method was chosen because temperature, charge rate, and discharge rate complicated the calculation, it was accessible, and it could be easily incorporated.

3.4.3 Optimum Sizing of SAPV Systems

Sizing Method

The sizing methodology chosen in this section must allow for energy sharing between individual SAPV systems without becoming too complex. From the literature survey, there are 6 possible sizing methodologies for SAPV systems: Intuitive, Numerical, Analytical, Commercial Software, Intelligent, and Hybrid. Each of the above

mentioned methods for optimal sizing of an SAPV system has limitations that can be summarized as shown in Table 3.3.

Table 3.3. Limitations of SAPV Sizing Methodologies

SAPV Sizing Methodology	Time-step	Limitations
Intuitive	Daily and Monthly	Simplified calculation based on daily or monthly meteorological data, leads to over/under sizing of system design, low reliability, increased system capital, maintenance and operation costs
Numerical	Hourly, Daily, and Monthly	Suboptimal solutions reached as computation involves linear changes of the decision variables
Analytical	Hourly, Daily, and Monthly	Less flexible, requires calculating coefficients for each location
Software	Hourly, Daily, and Monthly	Unable to improve system components and change component specifications. Unable to add energy trading functionality
Artificial Intelligence	Hourly, Daily, and Monthly	Complexity in designing system components. Useful for estimating system performance where there is no historical data but U.S. has data available
Hybrid	Hourly, Daily, and Monthly	Even more complex than artificial intelligence methods. Unable to add energy trading functionality

Intuitive methods are only suitable for an initial or rough approximation of the SAPV requirements.

An analytical approach will not work for the proposed energy infrastructure because the model should be as generic as possible, not requiring calculation of geographical coefficients. Analytical methods also lack time simulation which is necessary for use in % PV Generation Utilization and Loss of Power Supply Probability calculations.

No existing software tool allows for optimization of SAPV systems which share energy.

Artificial intelligence methods are not ideal because they are overly complex and meteorological data is widely available across the US. As such, hybrid methods would also be too complex for this application.

A numerical approach was chosen for this thesis because it uses iterative loops and linear functions compared to complex algorithms and can easily incorporate varying

data such as solar radiation and residential load profiles. This method can be implemented through Matlab and there are several sources which will aid in the development of the model.

Technical Considerations

For the purposes of sizing the proposed energy infrastructure, technical considerations chosen include Loss of Power Supply Probability and % PV Generation Utilization.

LPSP is chosen over LLP because in the case of an SAPV system it is usually more accurate to say that the power supply was not adequate than to say that the load was too large. This is because the load is somewhat consistent (cyclic) from day to day but the supply (solar radiation) is not uniform.

LPSP is a tried and true method for sizing SAPV systems with a standard value of 0.1%. This means that out of 8,760 hours in a standard (non-Leap) year, it is acceptable for 8.76 hours (taken as 9 because of 1-hour time resolution) to have insufficient supply. LPSP is given by the ratio of all energy deficits to the total load demand during the considered period. [59, 60] The expression used for LPSP is:

$$LPSP = \frac{N_{OutageHours}}{N_{TotalHours}} \quad (3.5)$$

In this calculation it is important to notice that we are considering the time sensitivity of the variables and not the quantity of energy produced. It would be incorrect, for instance, to say that over a large time interval more energy is generated than consumed so LPSP must be equal to 0 without conducting time simulation to show if there is any moment where load demand is greater than energy available. An LPSP value equal to 0, means that the load demand is satisfied at all times for a specific time period (t). A value in between 0 and 1 means that the supply does not meet load demand at all times due to either insufficient solar radiation and/or battery

storage capacity. An LPSP value of 1 would mean that the supply never meets load demand.

A familiar saying in energy efficiency is "You can't improve what you don't measure." Because it is expected that the utilization of solar energy will be improved due to the proposed energy infrastructure, % PV Generation Utilization will be calculated by the tool but will not be used in the optimization model. The purpose of including this feature is to, in the future, compare different cases and hopefully show that a higher percentage of the PV Generation is utilized using the proposed energy infrastructure.

% PV Generation Utilization is expressed as:

$$\%PVGenerationUtilization = \frac{\sum_{t=0}^{t=T} PVGenerationUtilized}{\sum_{t=0}^{t=T} TotalPVGeneration} \quad (3.6)$$

Economic Considerations

For the purposes of sizing our proposed energy infrastructure, capital cost will be the main consideration.

Capital cost is given as the total cost of the system including the cost for all solar panels, all batteries, their installation and hardware, and the cost of interconnection.

Although lifecycle cost and levelized cost of energy are useful economic parameters, they are not given directly by the model and require extra analysis.

3.5 Validation

This section describes how the model is validated by using an outside source (HOMER), several other validation tests, and by giving the functions artificial inputs and checking that they give the desired output.

HOMER was chosen for the validation because it is the world's leading microgrid modeling software, it performs a similar analysis to the proposed model (hourly numerical analysis), it was accessible, the author had some experience with HOMER,

and the inputs could be easily matched. No existing commercial software allows for transactive microgrid modeling or simulation of trading between systems. Because HOMER can not simulate an energy trading system or more than one residential system, it can only be used to verify the Baseline (Isolated Consumption) case.

HOMER was setup according to the following specifications:

- Tesla Powerwall 2.0 from complete energy storage catalog. Changed Capital Cost to \$ 8,100, the search space to integers from 1 - 30, and changed the initial state of charge for the different cases. Included a 'Large free Converter' component to model the integrated inverter.
- Imported the same load and solar data used in this model. Noted that the load data is somewhat larger than HOMER's initial estimate for the same location but my data includes electric heating.
- Used the 'Generic flat plate PV' component for the PV generation. Changed the PV capacity to 3 kW, capital cost to \$8,377, Derating Factor to %73.1, and edited the search space to only give answers my model would look at. Did not consider the effect of temperature.
- Case studies considered:
 - Geographic Locations = (Phoenix, Arizona; Little Rock, Arkansas; Indianapolis, Indiana; Erie, Pennsylvania)
 - Required Reliability = (0.1%, 1% LPSP)
 - Initial Charge = (10%, 20%, 100%)

These validation results are included in Table 3.4 which compares the results given the same inputs for this model's baseline case. My baseline case (one SAPV system without any energy trading capability) compares reasonably well with HOMER, with the largest difference being for Indianapolis.

Some reasons for discrepancies between the two models are that HOMER calculates reliability through capacity shortage (capacity loss / total capacity demanded) while I'm looking at hours (hours where capacity is lost/ 8760). HOMER does not consider the effect of starting month so June was taken as the starting month for my baseline model. It also may be due to the simulation model, battery model, and better optimization model of HOMER. HOMER selects an optimum configuration while this thesis's model takes an average of all the trials. This is why HOMER gives an integer value for number of batteries while this thesis's model does not.

The next list describes other successful validation tests completed, mainly to confirm that `Baseline_ESS_Analysis`, `Central_ESS_Analysis` and `IES_Analysis` give expected results under artificial conditions:

- `Baseline_ESS_Analysis` simulates the systems one by one, `IES_Analysis` handles each system concurrently. Commented out the trading system in `IES_Analysis` and confirmed that it gives the same results as `Baseline_ESS_Analysis`.
- Although `Central_ESS_Analysis` implements roughly the same code as `Baseline_ESS_Analysis` it uses the variable "Shared_Hourly_Load" instead of "Hourly_Load." Checked to make sure that `Central_ESS_Analysis` gives the same results as `Baseline_ESS_Analysis` when given the same load.
- Checked that `Central_ESS_Analysis` and `IES_Analysis` give the same results as baseline when only one system is considered.

The final list describes the functions validated by choosing inputs that should give an expected output. These functions are given as they are in Matlab with the format: `[OUTPUT] = Function_Name(INPUT)`.

- `[Solar_Data, Load_Data] = TMY3_Input(Monthpoint)`

Table 3.4. HOMER Validation

Method	Location	Required Reliability (%)	Initial Charge (%)	Solar Panels (#)	Batteries (#)	Capital Cost (\$)
HOMER	Phoenix,AZ	0.1	10	6	3	\$ 74,562
Baseline	Phoenix,AZ	0.1	10	5	3.2	\$ 67,805
HOMER	Phoenix,AZ	0.1	20	6	3	\$ 74,562
Baseline	Phoenix,AZ	0.1	20	5	3.1	\$ 67,319
HOMER	Phoenix,AZ	0.1	100	6	3	\$ 74,562
Baseline	Phoenix,AZ	0.1	100	5	3	\$ 66,995
HOMER	Phoenix,AZ	1	10	5	3	\$ 66,185
Baseline	Phoenix,AZ	1	10	4	3	\$ 58,051
HOMER	Phoenix,AZ	1	20	5	3	\$ 66,185
Baseline	Phoenix,AZ	1	20	3	3	\$ 57,970
HOMER	Phoenix,AZ	1	100	5	3	\$ 66,185
Baseline	Phoenix,AZ	1	100	4	3	\$ 57,808
HOMER	Erie,PA	0.1	10	13	3	\$ 133,201
Baseline	Erie,PA	0.1	10	13	3.1	\$ 134,011
HOMER	Erie,PA	0.1	20	12	3	\$ 124,824
Baseline	Erie,PA	0.1	20	13	3	\$ 133,444
HOMER	Erie,PA	0.1	100	12	3	\$ 124,824
Baseline	Erie,PA	0.1	100	13	3.1	\$ 133,768
HOMER	Erie,PA	1	10	12	2	\$ 116,724
Baseline	Erie,PA	1	10	12	2.3	\$ 118,992
HOMER	Erie,PA	1	20	12	2	\$ 116,724
Baseline	Erie,PA	1	20	12	2.2	\$ 118,020
HOMER	Erie,PA	1	100	12	2	\$ 116,724
Baseline	Erie,PA	1	100	12	2.2	\$ 118,263
HOMER	Indianapolis,IN	0.1	10	9	4	\$ 107,793
Baseline	Indianapolis,IN	0.1	10	10	4.5	\$ 120,301
HOMER	Indianapolis,IN	0.1	20	10	3	\$ 108,070
Baseline	Indianapolis,IN	0.1	20	10	4.5	\$ 120,625
HOMER	Indianapolis,IN	0.1	100	7	4	\$ 91,039
Baseline	Indianapolis,IN	0.1	100	10	4.4	\$ 119,410
HOMER	Indianapolis,IN	1	10	7	3	\$ 82,939
Baseline	Indianapolis,IN	1	10	9	3.5	\$ 104,067
HOMER	Indianapolis,IN	1	20	7	3	\$ 82,939
Baseline	Indianapolis,IN	1	20	9	3.4	\$ 103,257
HOMER	Indianapolis,IN	1	100	7	3	\$ 82,939
Baseline	Indianapolis,IN	1	100	9	3.5	\$ 103,986
HOMER	LittleRock,AR	0.1	10	11	5	\$ 132,647
Baseline	LittleRock,AR	0.1	10	10	5	\$ 124,270
HOMER	LittleRock,AR	0.1	20	11	5	\$ 132,647
Baseline	LittleRock,AR	0.1	20	10	5.1	\$ 124,837
HOMER	LittleRock,AR	0.1	100	8	7	\$ 123,716
Baseline	LittleRock,AR	0.1	100	10	4.8	\$ 122,812
HOMER	LittleRock,AR	1	10	8	4	\$ 99,416
Baseline	LittleRock,AR	1	10	9	3.7	\$ 105,120
HOMER	LittleRock,AR	1	20	8	4	\$ 99,416
Baseline	LittleRock,AR	1	20	9	3.7	\$ 105,201
HOMER	LittleRock,AR	1	100	8	4	\$ 99,416
Baseline	LittleRock,AR	1	100	9	3.6	\$ 104,877

- Here there is only one input to test, Monthpoint. Different values were input and confirmed that the expected Solar and Load Data is output. For example, choosing a value for Monthpoint of either -744 or 8,016 coincides with data beginning on February 1st at 1 AM, as expected.
- [Maximum_Solar, Big_Cumulative_STM] = Solar_Cumulative_STM_Generator(Solar_Data)
 - Again, there is only one input. Solar Data can be chosen so that there is an expected output and the function is validated. For example, Solar Data with a repeating sequence of (0, 9, 18, 27, 36, 45) was input, Maximum_Solar and Big_Cumulative_STM gave expected output. These values were chosen because it confirms that the model rounds the numbers as expected.
- Solar = Solar_Irradiation_Simulator(Number_of_Trials, Simulation_years, Maximum_Solar, Big_Cumulative_STM)
 - Similar to the previous function, the same repeating sequence of (0, 9, 18, 27, 36, 45) was input. Solar gave expected results going from 0 to 10 to 20 to 30 to 40 to 50 and back 0 for the time period of Simulation_Years and the correct number of trials. This validation is shown in Figure 3.9.
- [PV_Output, Total_PV_Generation] = PV_Output_Calculator(Solar, Number_of_Trials, Solar_Panel_Range, Solar_Panel_Rating, PV_Derating_Factor)
 - Confirmed that 'Total_PV_Generation' accurately calculates the total PV generated by 'PV_Output' over the year. In Excel, the values of PV Output are summed for the year and compared them with the model output, both giving the correct output of 1,095.
 - Confirmed that 'PV_Output' gives realistic values that compare reasonably with the source data set.

- Confirmed both outputs for the sequence of (0, 9, 18, 27, 36, 45) for redundancy and ability to manually reproduce the solution. Using a PV derating factor of 0.5 and a PV rating value of 1 kW values sequence as expected (0, 0.5, 10, 15, 20, 0), shown in Figure 3.9.
- [Hourly_Load, Shared_Hourly_Load] = Load_Demand_Simulator(Number_of_Trials, Number_of_SAPV_Systems, Simulation_Years, Load_Data)
 - Confirmed that Hourly Load is shifted as expected, that Shared_Hourly_Load calculates the sum correctly, and that the function correctly considers the Number_of_Trials, Number_of_SAPV_Systems, and Simulation_Years.

3.6 Summary

In summary, this chapter described the methodology for comparing energy sharing strategies in detail, including the research design; inputs such as project specifications, component specifications, solar irradiation data, and residential load data; procedures for simulating solar irradiation, simulating residential loads, predicting PV and ESS performance, predicting energy infrastructure performance, and optimally sizing of SAPV; outputs such as Loss of Power Supply Probability, % PV Generation Utilization, and Capital Cost; explanation of the code through flowcharts and variable descriptions; validation methods; analysis methods; and summary. In the next section, results will be generated according to the research design and will be discussed to show the differences in isolated consumption (baseline), CES, and IES. A summary table will be assembled which focuses on the optimum configuration found based on total cost.

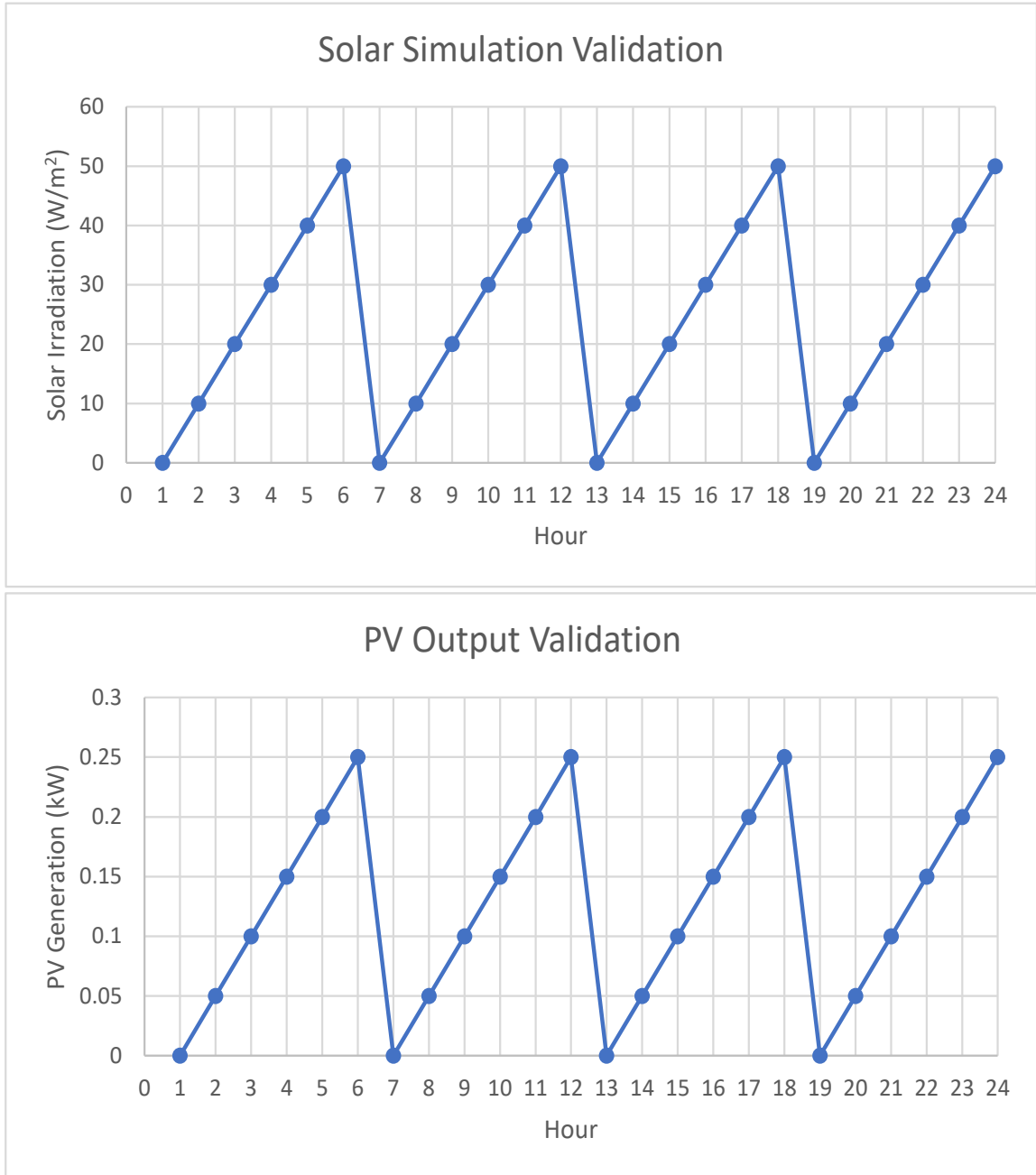


Figure 3.9. Solar simulation and PV generation validation. Shows one 24 hour period where values go as expected from the repeated solar data input of (0, 9, 18, 27, 36, 45, 0). For the solar simulation values proceed in the following sequence (0, 10, 20, 30, 40, 50, 0) and for PV generation (0, 0.05, 0.1, 0.15, 0.2, 0.25, 0) with 0.5 PV derating factor, 1 solar panel, and 1 kW Solar Panel Rating.

4. RESULTS AND DISCUSSION

4.1 Results for Varying Initial Charge

The Baseline case corresponds with one isolated SAPV system which uses the conventional SAPV sizing strategy and does not have energy sharing capability.

Based on the figures in this section, the effect of initial charge is not very prevalent in July (Figures 4.1 - 4.3) or March (Figures 4.4 - 4.6), but is much more appreciable in November (Figures 4.7 - 4.9). More research is needed to show how initial charge might affect the rest of the months in the year.

In the November case the lower initial charges of 1% and 5% have a higher cost, presumably due to difficulties generating enough power to bounce back from the initial charge condition. It does not appear that any operating strategy handles a low initial charge condition better than the others.

In the March and July cases for all three operating strategies every initial charge condition gives roughly the same cost, showing that there was abundant solar power available to recover from the initial charge condition.

The cases of 1%, 5% and 100% initial charge show more varied results but are not likely scenarios in the real world. The purpose of including these cases was to show that initial charge could have a more pronounced effect. From the Components Specification section, a lithium ion battery must be shipped with less than 30% charge and there are losses that occur before reaching the customer. Typical values for initial charge are between 5% and 20% based on Tesla customer surveys. 10% was chosen as the baseline for the rest of the simulation.

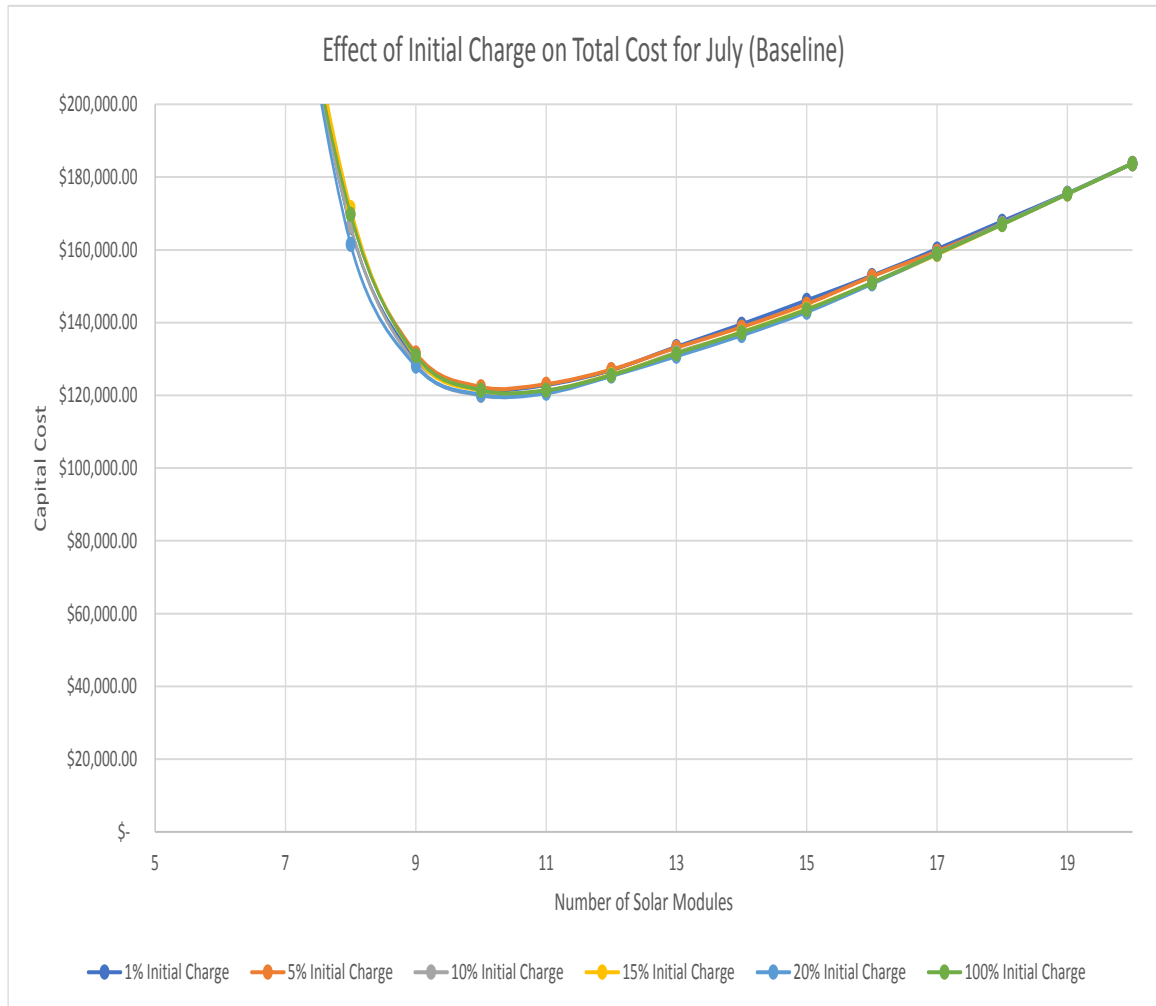


Figure 4.1. Results for Baseline case with varying initial charge given July, 5 systems, Indianapolis, and 0.1% LPSP

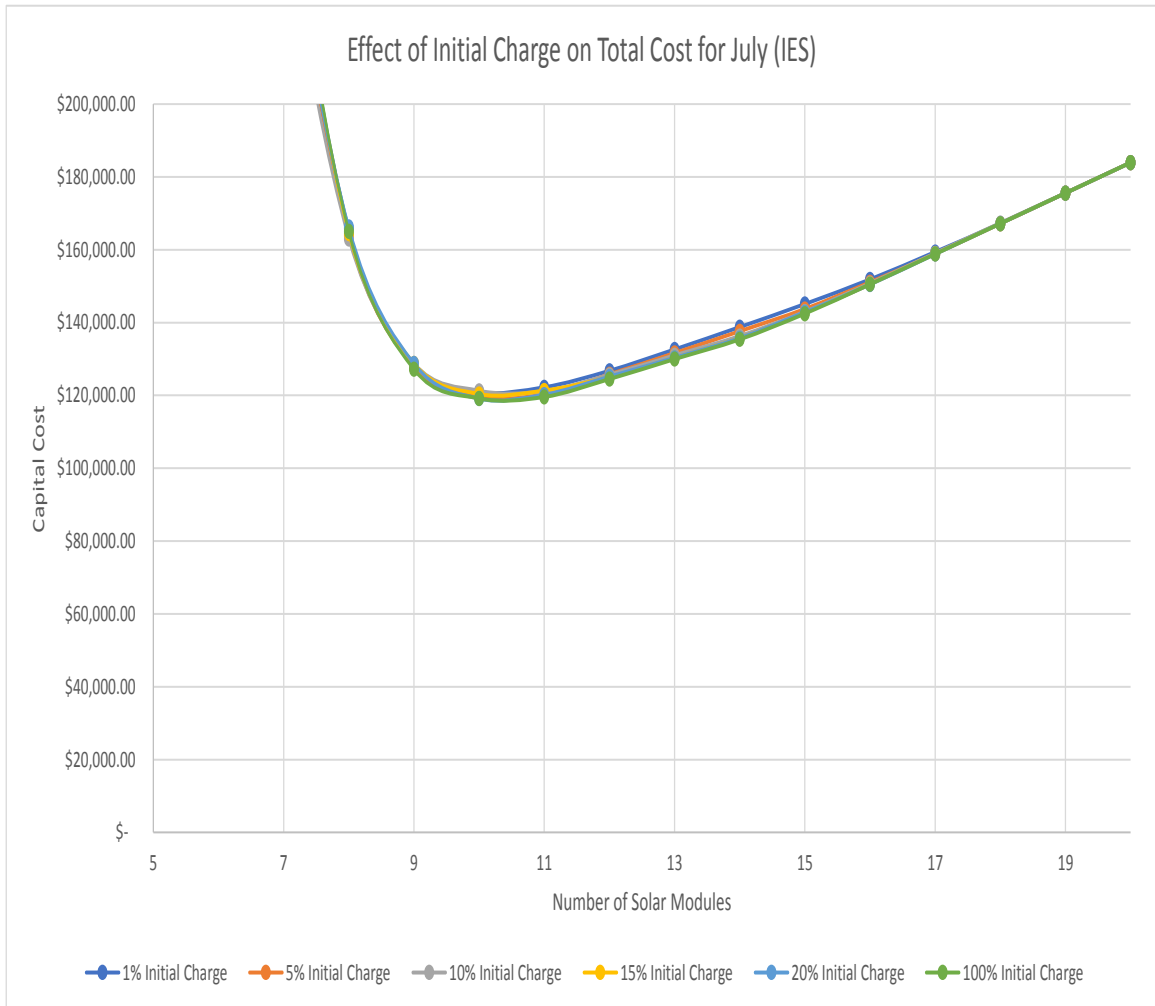


Figure 4.2. Results for IES case with varying initial charge given July, 5 systems, Indianapolis, and 0.1% LPSP

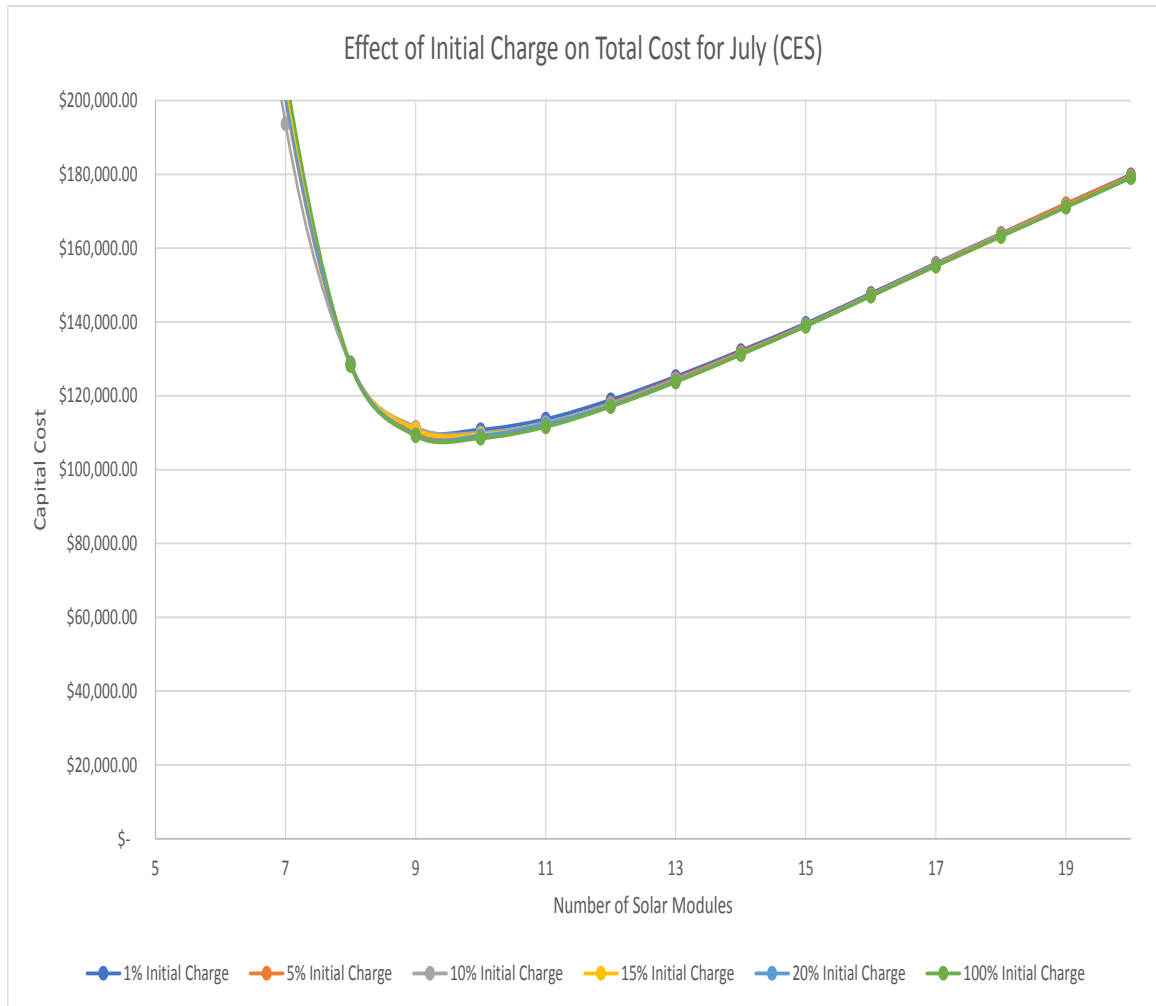


Figure 4.3. Results for CES case with varying initial charge given July, 5 systems, Indianapolis, and 0.1% LPSP

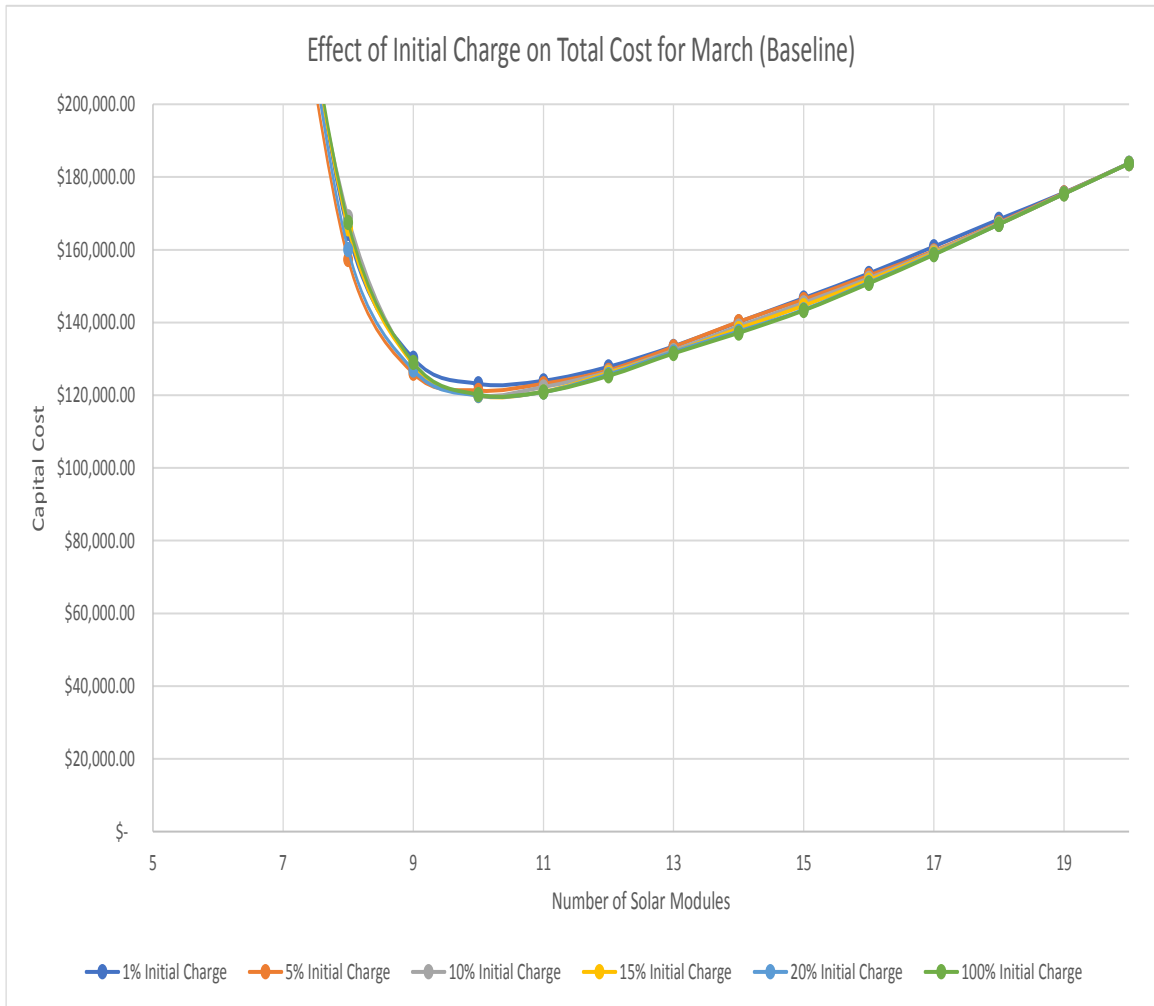


Figure 4.4. Results for Baseline case with varying initial charge given March, 5 systems, Indianapolis, and 0.1% LPSP

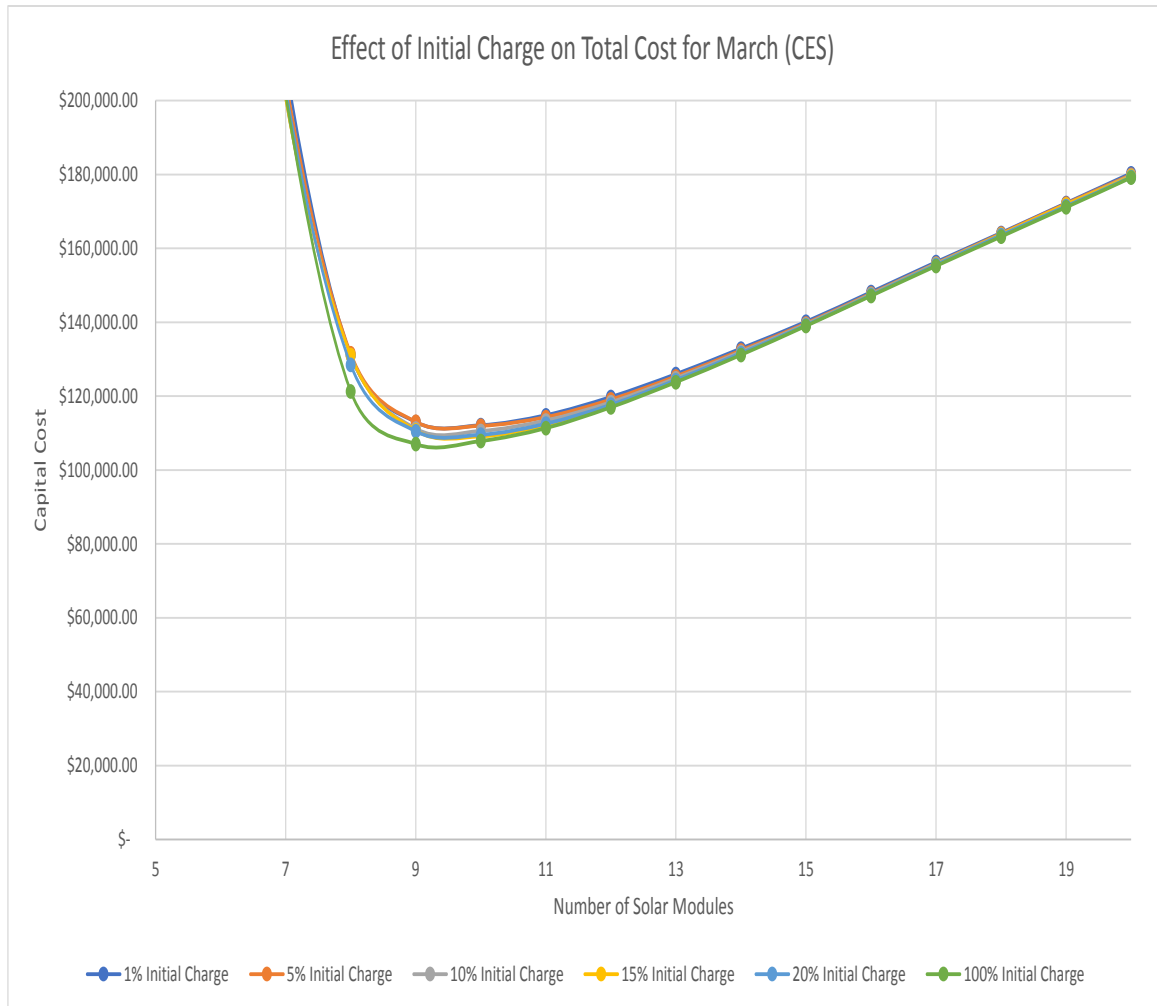


Figure 4.5. Results for CES case with varying initial charge given March, 5 systems, Indianapolis, and 0.1% LPSP

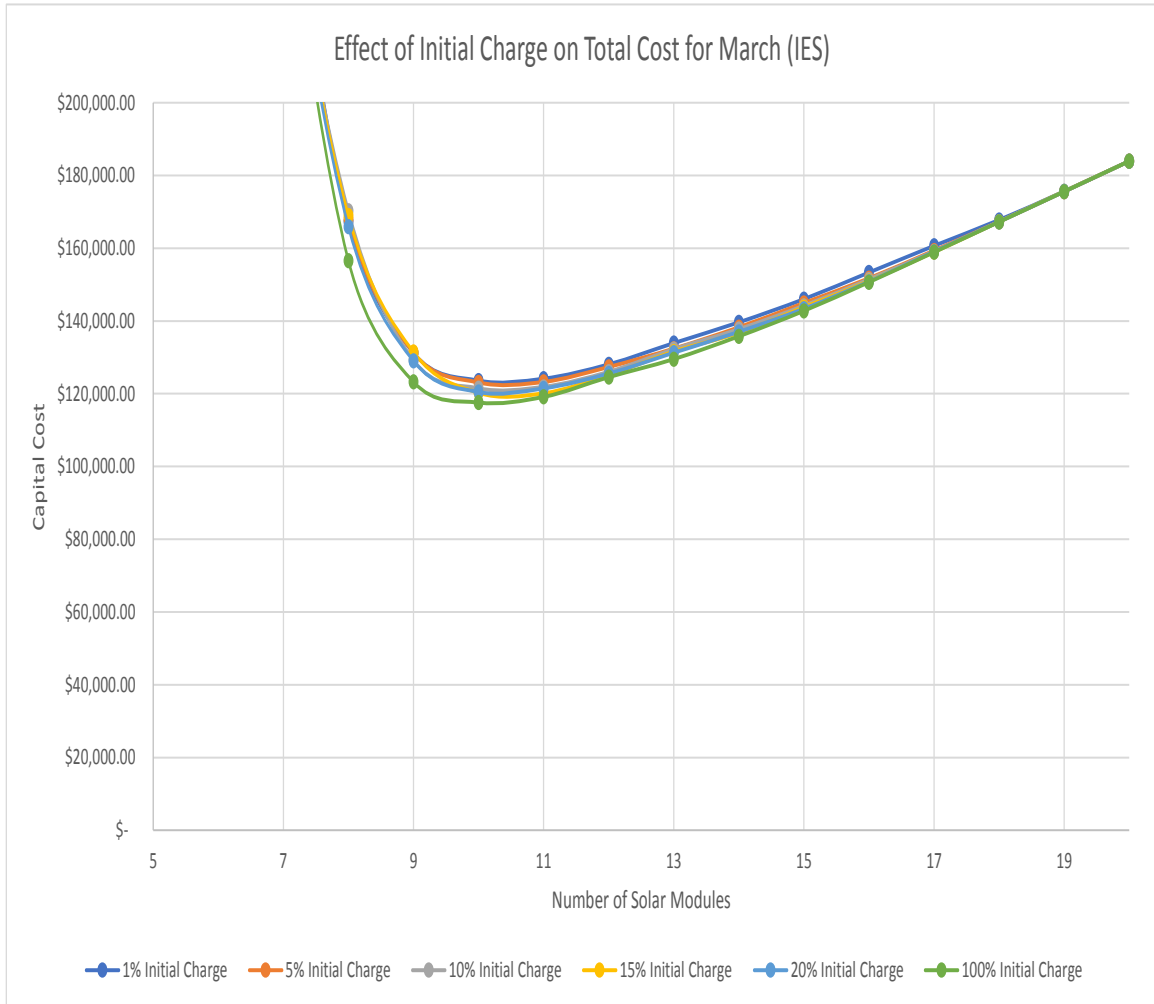


Figure 4.6. Results for IES case with varying initial charge given March, 5 systems, Indianapolis, and 0.1% LPSP

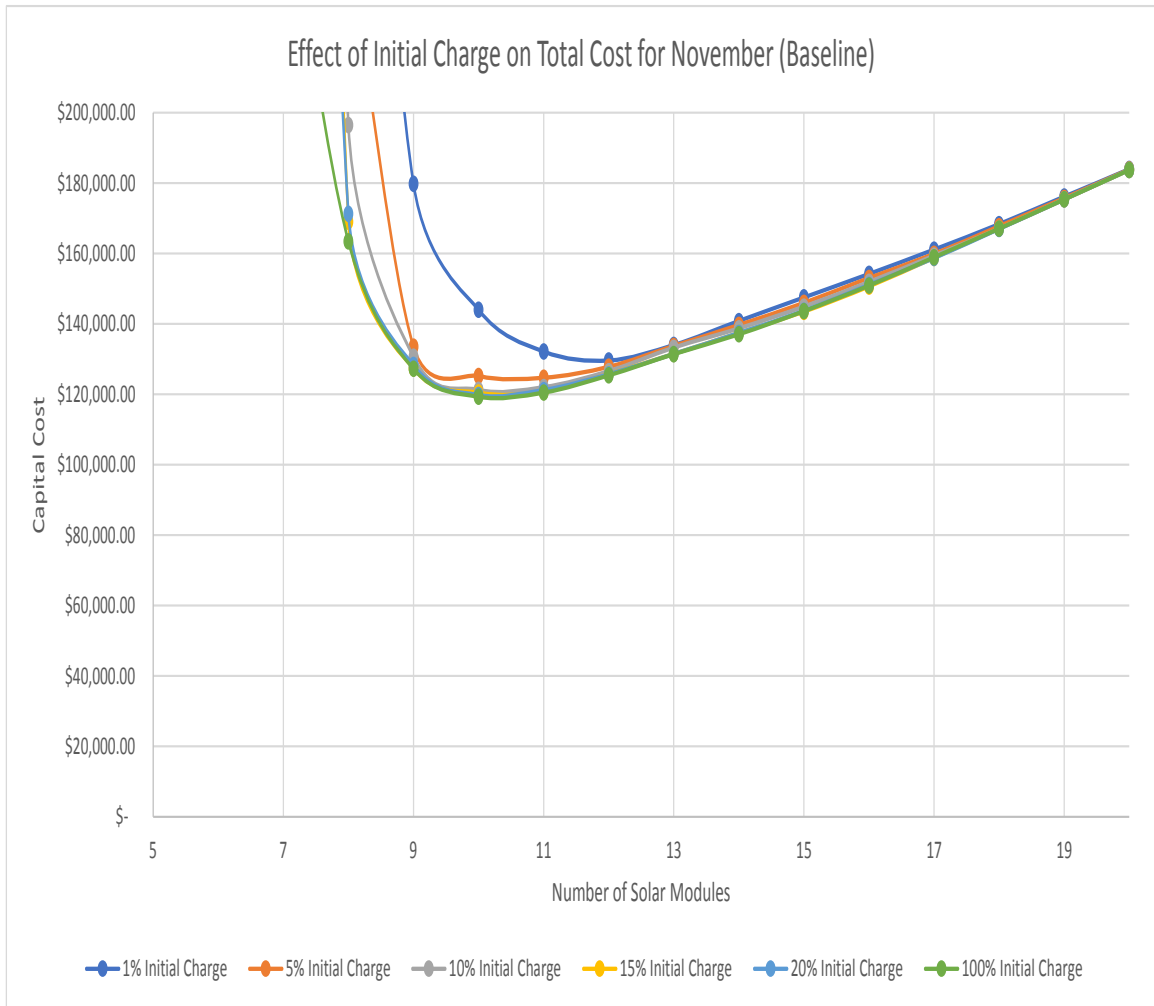


Figure 4.7. Results for Baseline case with varying initial charge given November, 5 systems, Indianapolis, and 0.1% LPSP

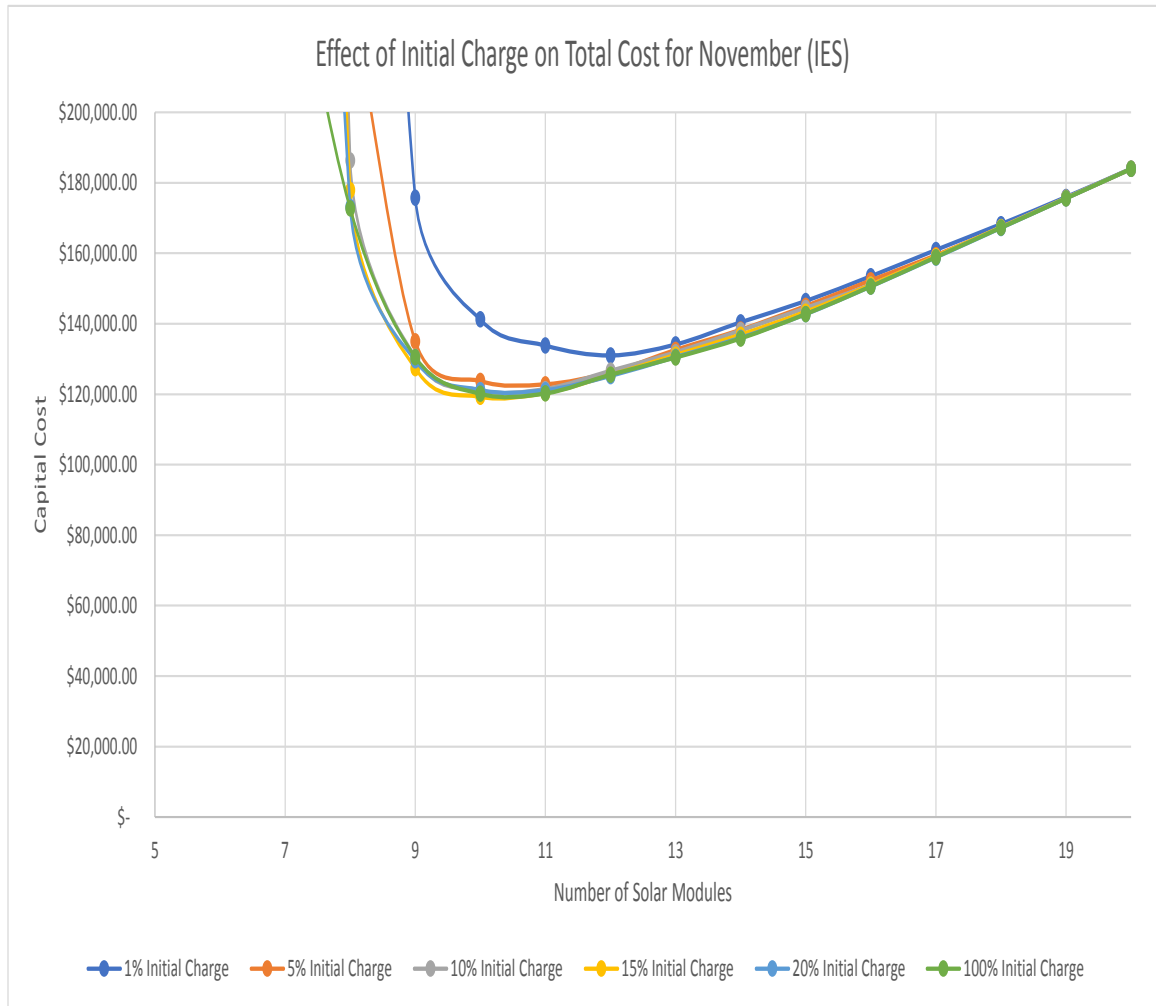


Figure 4.8. Results for IES case with varying initial charge given November, 5 systems, Indianapolis, and 0.1% LPSP

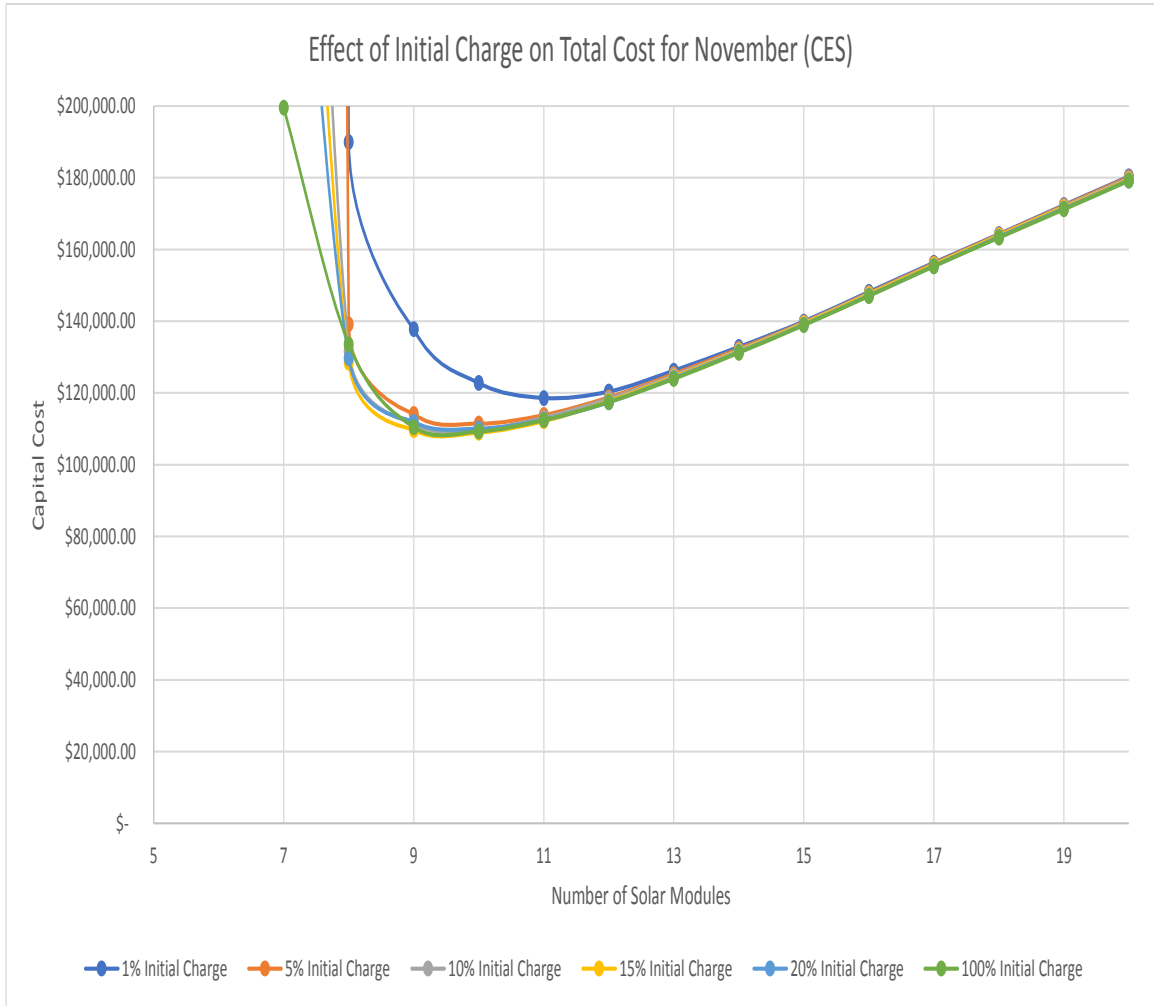


Figure 4.9. Results for CES case with varying initial charge given November, 5 systems, Indianapolis, and 0.1% LPSP

4.2 Results for Varying Starting Month

Based on the figures in this section the months of January, February, March, July, and December give non-typical results compared to the rest of the months, which compare very reasonably. Indianapolis (Figures 4.10 - 4.12) and San Antonio (Figures 4.13 - 4.15) did not show the same effect for every month. Comparing both geographic location results, the month of June was selected as the baseline month for the rest of the simulation. Choosing July as the baseline was the original plan but this might introduce a small bias in favor of going off-grid.

HOMER does not include a method for analyzing the starting month of the simulation. These results indicate that starting month should be considered when a system wants to go off-grid especially in the winter months. If you must go off-grid during a winter month, it may be worth using a generator or external power source to increase the initial charge of the battery.

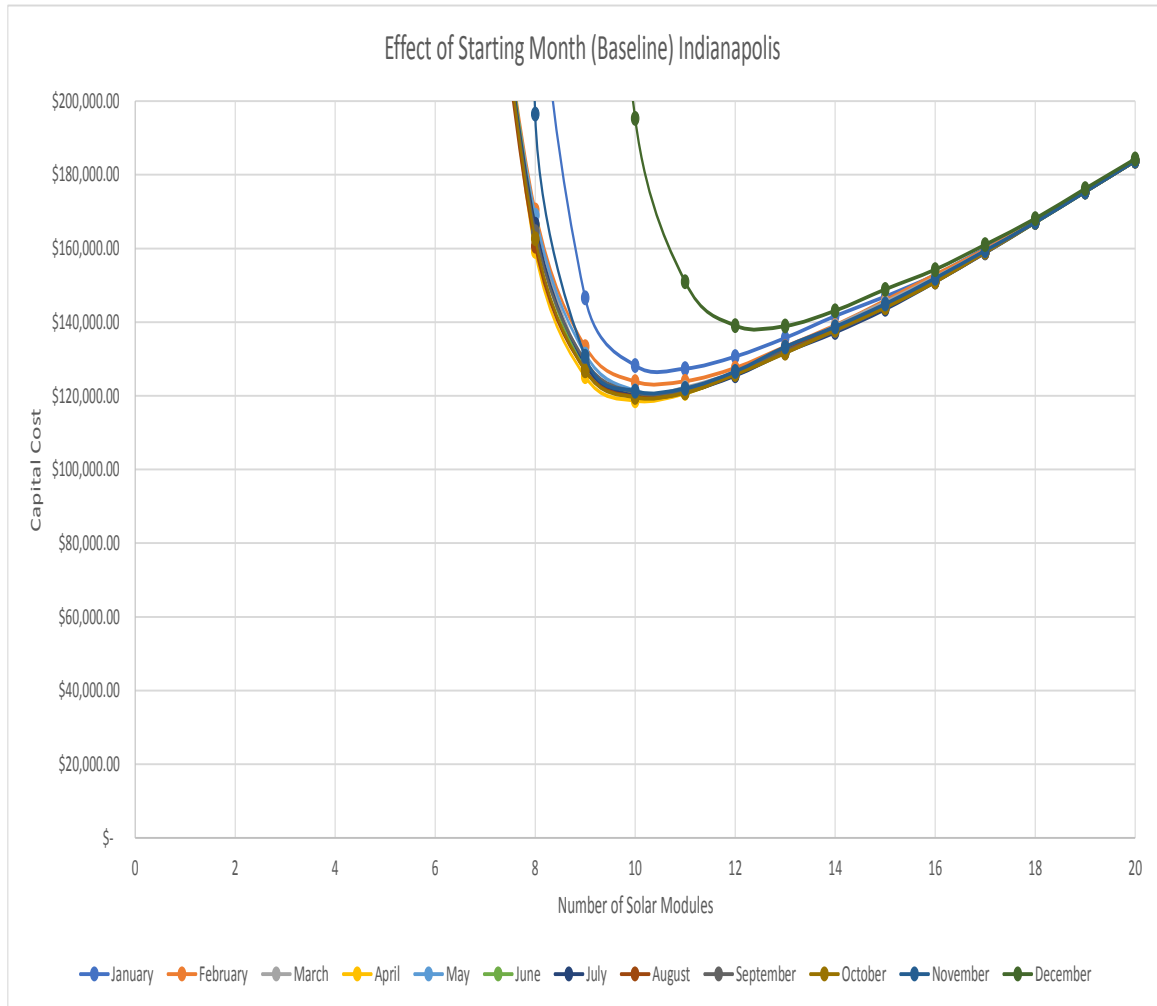


Figure 4.10. Results for Baseline case with varying starting month given 10% initial charge, 5 systems, Indianapolis, and 0.1% LPSP

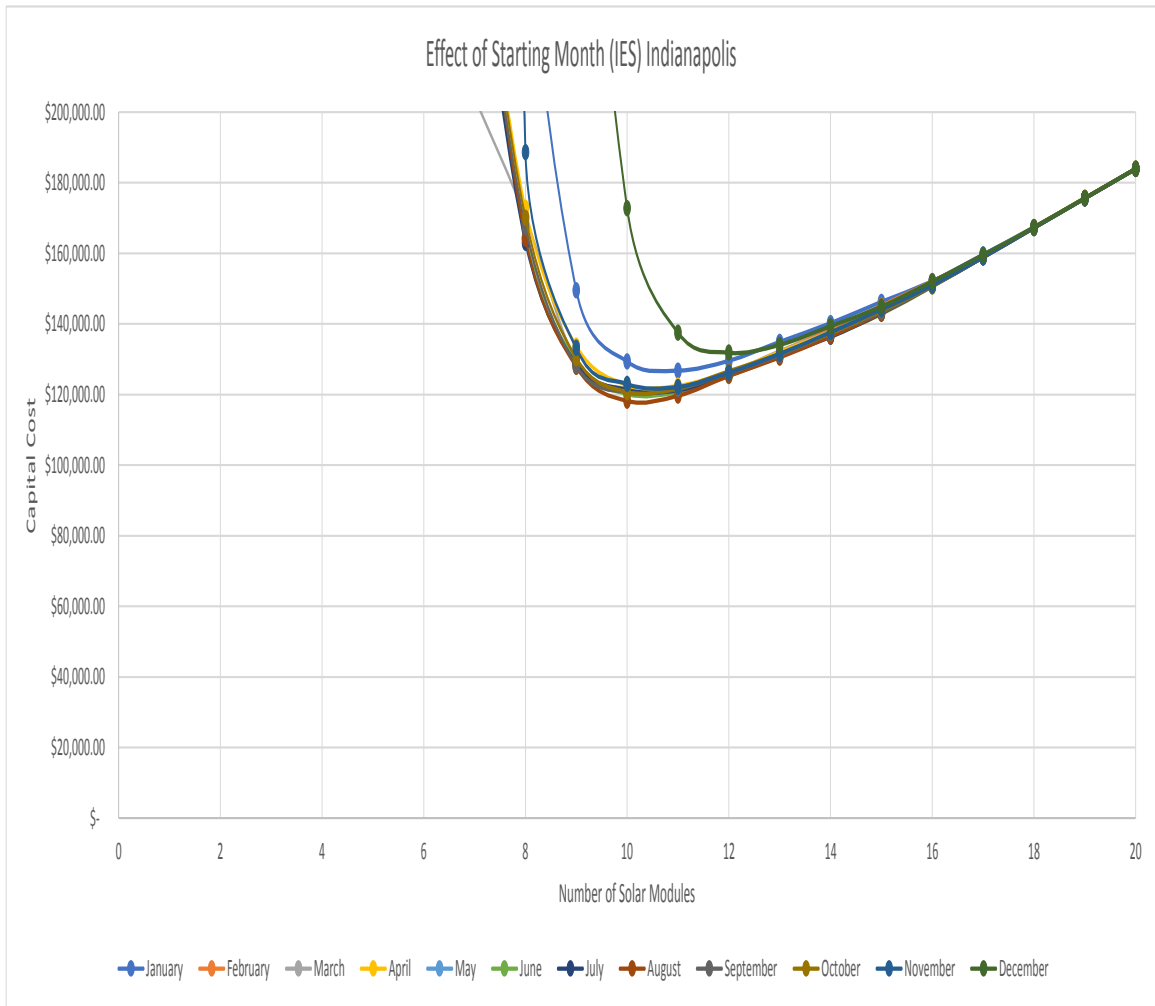


Figure 4.11. Results for IES case with varying starting month given 10% initial charge, 5 systems, Indianapolis, and 0.1% LPSP

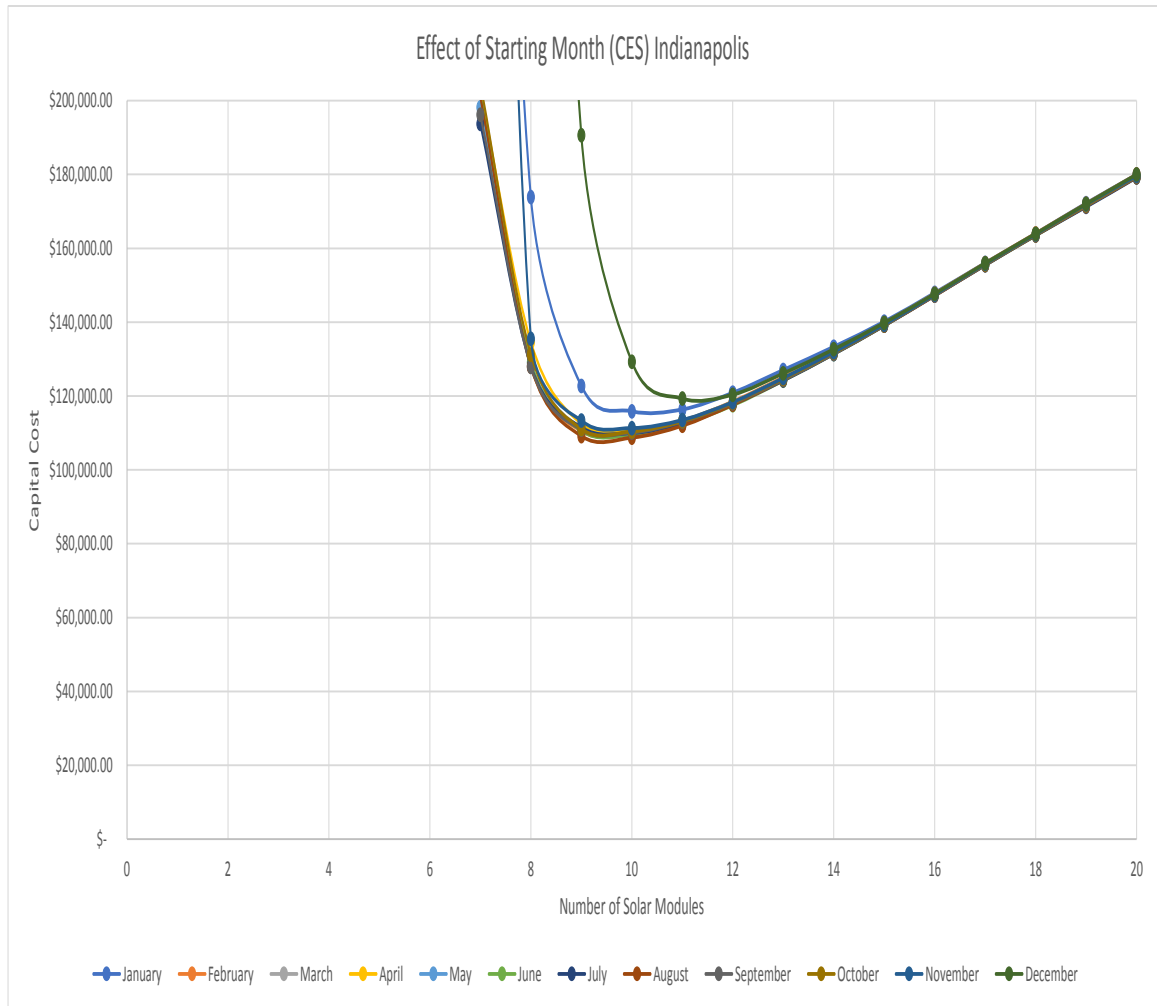


Figure 4.12. Results for CES case with varying starting month given 10% initial charge, 5 systems, Indianapolis, and 0.1% LPSP

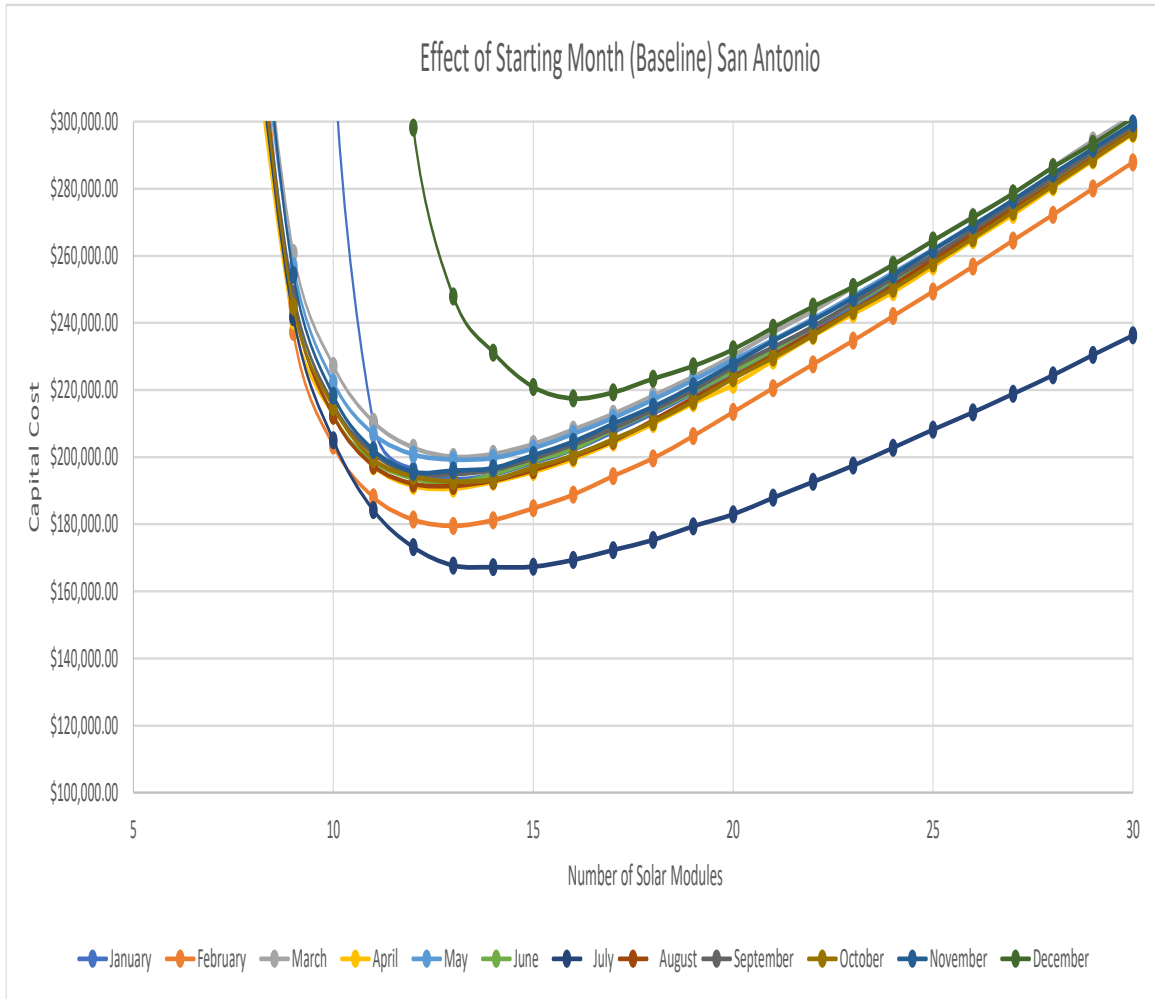


Figure 4.13. Results for varying starting month given 10% initial charge, 5 systems, San Antonio, and 0.1% LPSP. Note the change in scale compared to other results

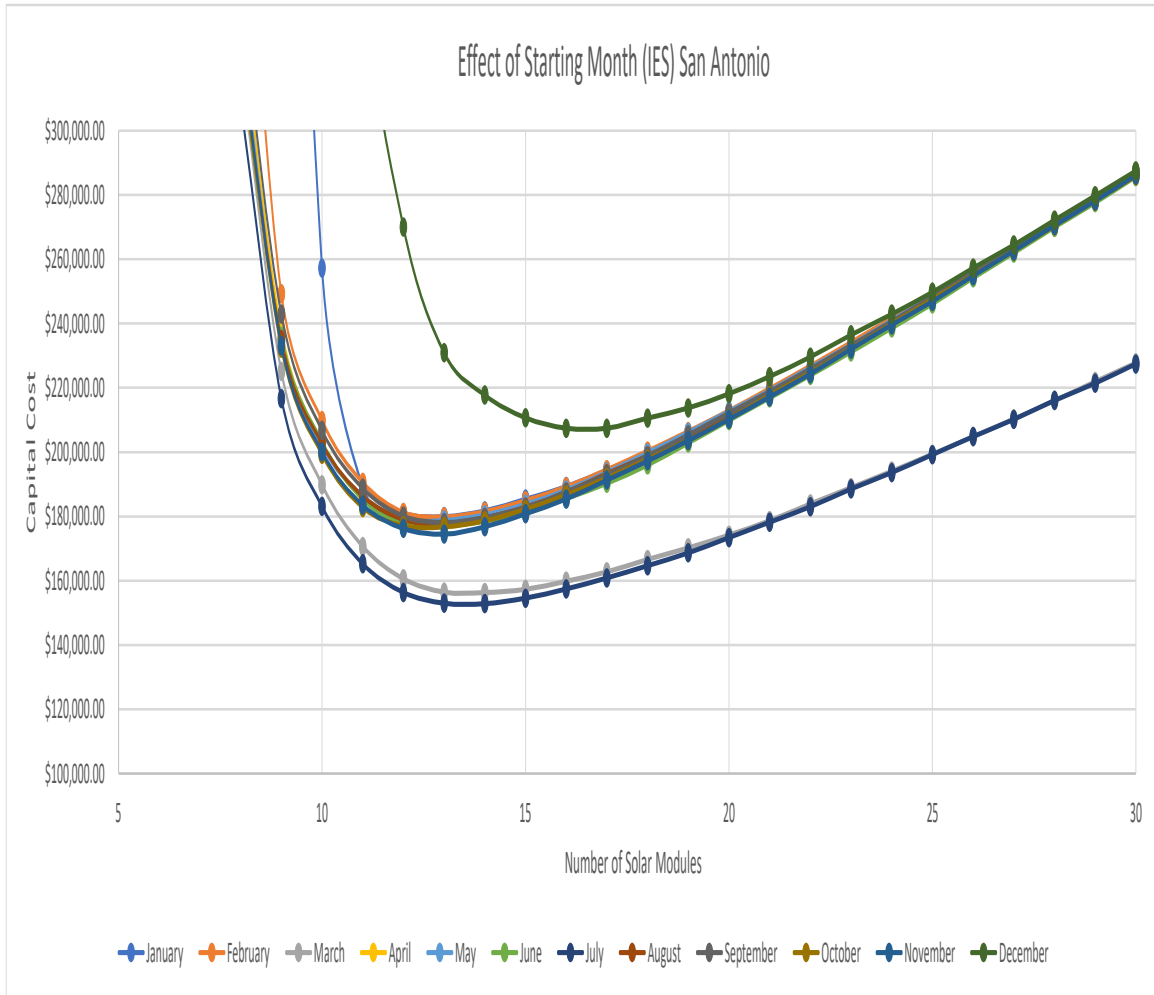


Figure 4.14. Results for varying starting month given 10% initial charge, 5 systems, San Antonio, and 0.1% LPSP. Note the change in scale compared to other results

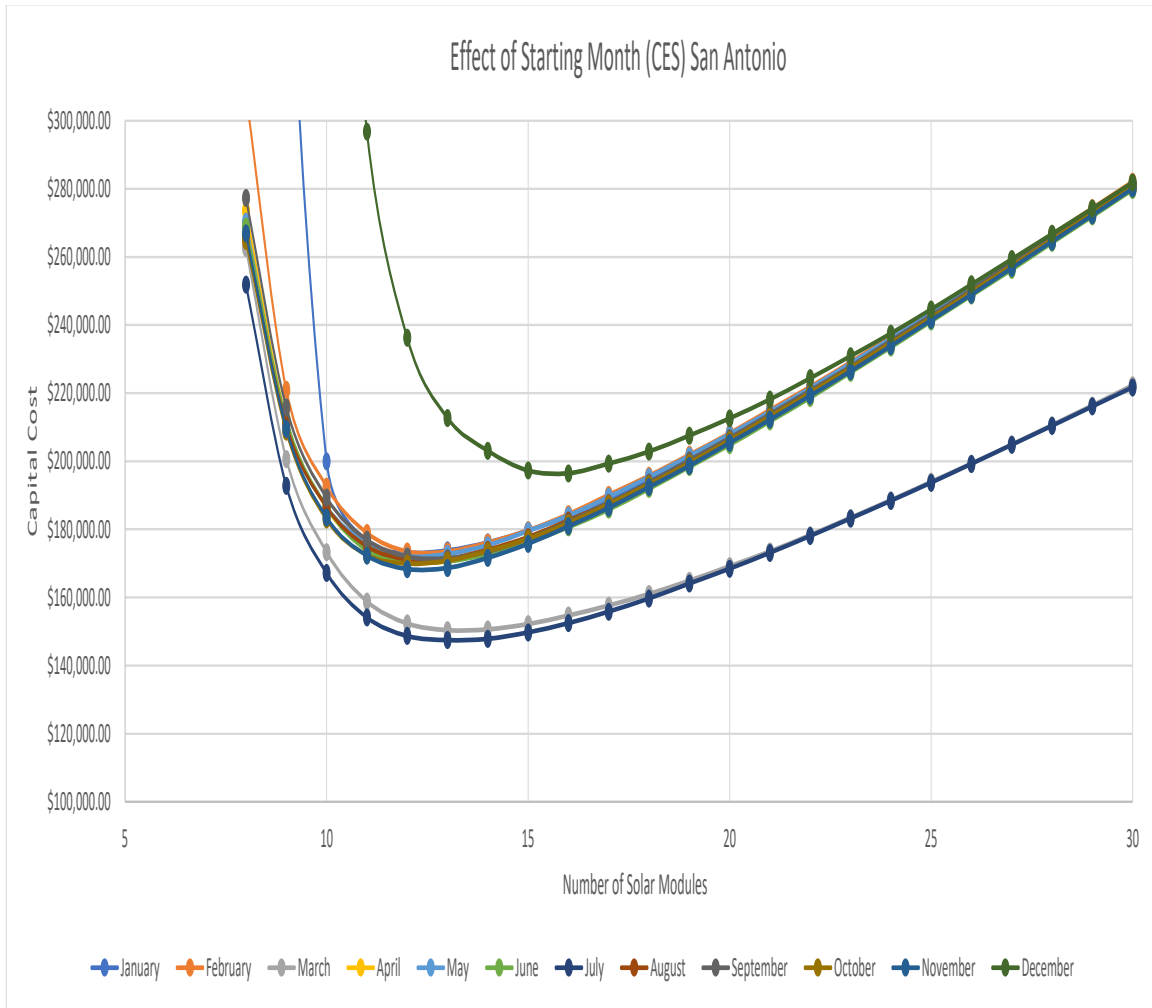


Figure 4.15. Results for varying starting month given 10% initial charge, 5 systems, San Antonio, and 0.1% LPSP. Note the change in scale compared to other results

4.3 Results for Varying Load Variability

Varying load variability for San Antonio (Figure 4.16) suggests that the capital cost is lower in both the CES with variability and IES with variability cases. For IES without load variability it's immediately clear that there is no purpose in establishing a transactive microgrid because it costs more than the baseline case. Ideally, load variability would greatly decrease the capital cost so that systems that are not on the same schedule have a chance to save money by joining together. The no variability case is not a realistic situation, there will almost surely be some load variability between residents.

These results are not consistent when geographic location is changed to Indianapolis (Figure 4.17) which indicates that more simulations are required to determine the effect of load variability. For this locations data, there does not seem to be much difference at all between the cases with variability and without.

There are better solutions for introducing load variability but it is not an easy question to determine how a residential load typically varies or how much the load was varied in a specific case. More advanced load simulation should be included so that load is not simply shifted to introduce variability.

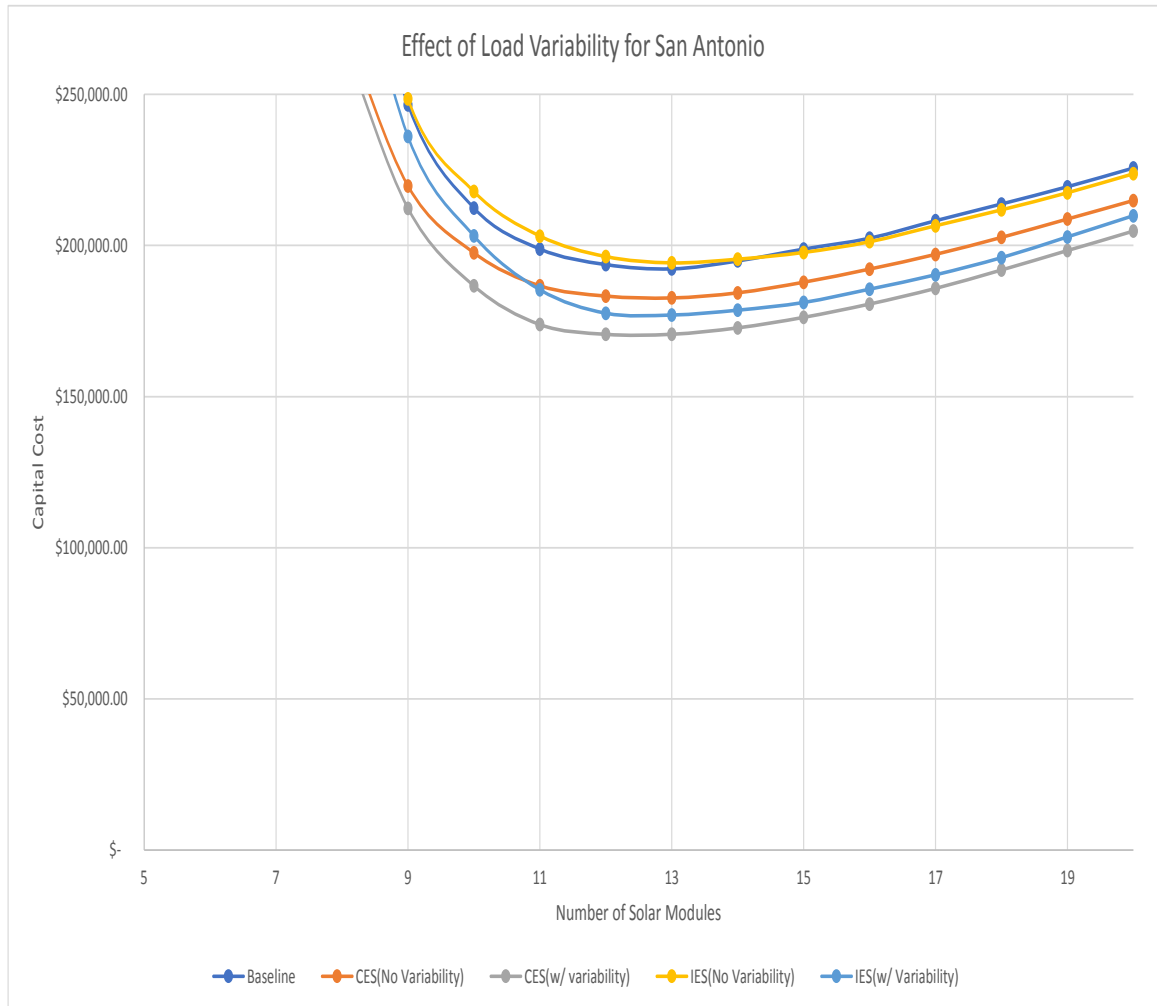


Figure 4.16. Results for varying load variability given June, 10% initial charge, 5 systems, San Antonio, and 0.1% LPSP

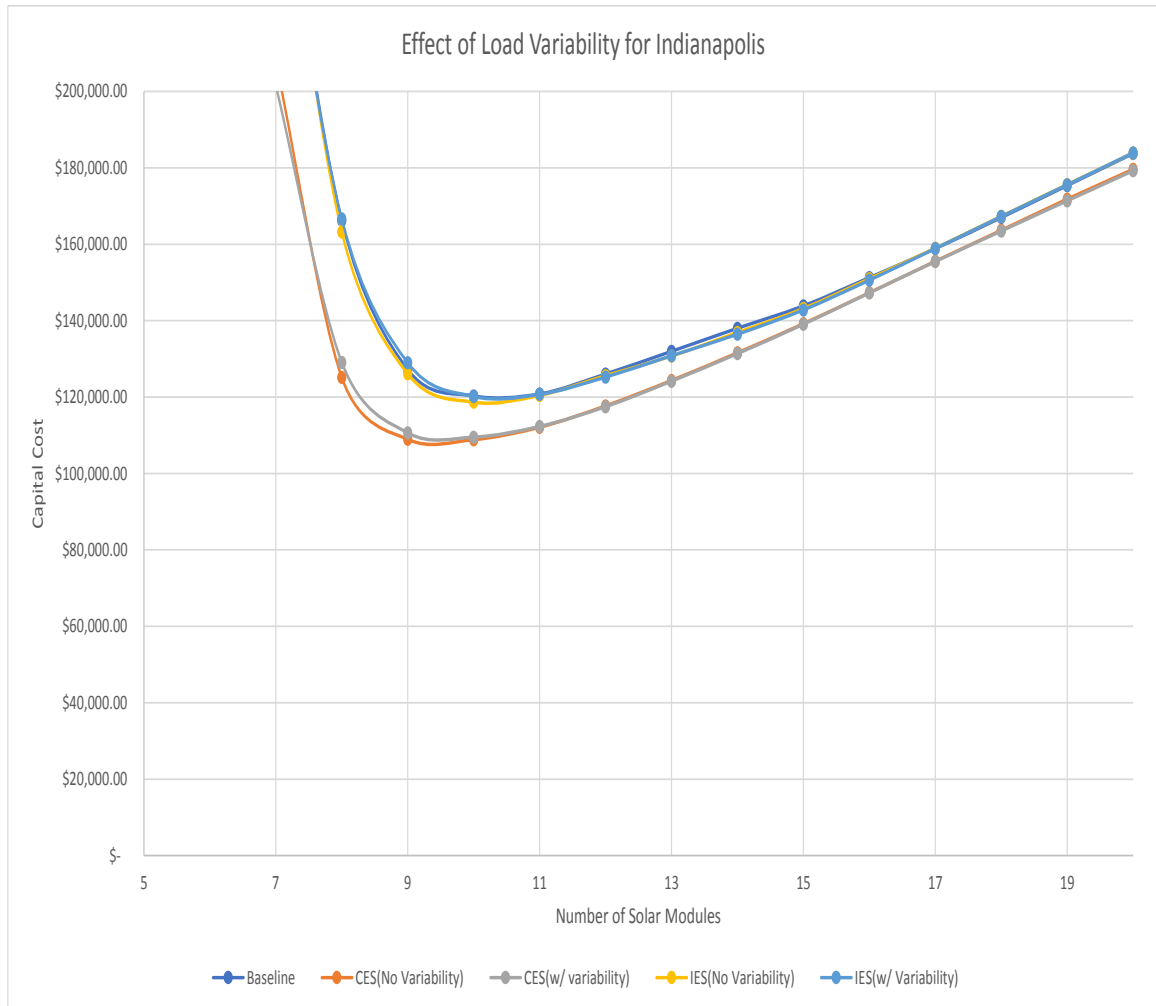


Figure 4.17. Results for varying load variability given June, 10% initial charge, 5 systems, Indianapolis, and 0.1% LPSP

4.4 Main Simulation

4.4.1 Effect of Number of Systems

The effect of the number of systems on total cost is explored in Figures 4.23 - 4.26, 4.32 - 35, 4.41 - 4.44, and 4.50 - 4.53.

The number of systems did not have a consistent or significant effect on total cost per system. This is contrary to the hypothesis that increasing the number of systems would reinforce the infrastructure because of more systems being available for trading. Considering that the IES case performs consistently better than the baseline with an interconnection cost included suggests that the IES case does provide a cost savings, its just not very much. More research is required with a better load simulation method to verify this result.

Interestingly, the centralized case showed similar savings for two systems and fifty systems, indicating that you don't need to increase the number of systems to find savings. This is promising because it's much easier to find just one other person to establish a microgrid with than to find fifty like-minded individuals and the lower combined capital cost might not require a company to step in.

4.4.2 Effect of Required Reliability

The effect of the required reliability on total cost is explored in Figures 4.18 - 4.22, 4.27 - 4.31, 4.36 - 4.40, and 4.45 - 4.49.

Changing LPSP required had a significant predictable effect in that as you relax the requirement the total cost per system goes down. Because the cost is so high, it is likely that sacrificing reliability and changing energy consumption habits will be required to make going off-grid affordable. Lower levels of required reliability should be considered to determine how low reliability would have to be for competitive pricing with GCPV systems.

4.4.3 Effect of Geographic Location

The effect of geographic location is explored for Indianapolis (Figures 4.18 - 4.26), Erie (Figures 4.27 - 4.35), Phoenix (Figures 4.36 - 4.44), and Little Rock (Figures 4.45 - 4.53). A summary table for each geographic location (Indianapolis Table 4.1, Erie Table 4.2, Phoenix Table 4.3, and Little Rock Table 4.4) was developed based on these figures.

Each location had a unique typical optimum range of solar panels and batteries. This was expected because the locations were all chosen from different climate zones and have different levels of average solar irradiation.

The results show that it is considerably cheaper to go off-grid in Phoenix than in any of the other locations studied. The cases with the lowest cost per system found in this study were from Phoenix with 1% LPSP required.

Erie consistently had the highest cost for going off-grid. The cases with the highest cost per system found in this study were from Erie with 0.1% LPSP required.

4.4.4 Indianapolis

This section contains all case studies for the location of Indianapolis (Figures 4.18 - 4.26) with a corresponding summary table (Table 4.1). Indianapolis has a climate zone of 'Cold' and a global normal irradiance of 3.5 - 4.0 kWh/sq.m/day. Indianapolis fell somewhere in the middle of the geographic locations studied in terms of total cost per system.

Table 4.1. Summary Table for Indianapolis showing the optimum configurations for each case from the Main Simulation.

Summary Table for Indianapolis					
Operating Strategy	LPSP (%)	Number of Systems	Optimum # of Solar Panels	# of Batteries (Average)	Capital Cost (Average)
Baseline	0.1	-	10	4.5	\$ 120,301
Baseline	0.2	-	10	4.2	\$ 117,709
Baseline	0.5	-	10	3.3	\$ 110,662
Baseline	1	-	9	3.5	\$ 103,338
IES	0.1	2	10	4.4	\$ 119,691
IES	0.1	5	10	4.5	\$ 120,161
IES	0.1	10	10	4.3	\$ 119,035
IES	0.1	20	10	4.1	\$ 117,188
IES	0.1	50	10	4.2	\$ 117,630
IES	0.2	2	10	4	\$ 116,532
IES	0.2	5	10	4	\$ 116,435
IES	0.2	10	10	4.1	\$ 117,059
IES	0.2	20	10	3.9	\$ 115,884
IES	0.2	50	10	4	\$ 116,540
IES	0.5	2	10	3.2	\$ 109,931
IES	0.5	5	10	3.3	\$ 111,056
IES	0.5	10	10	3.2	\$ 109,769
IES	0.5	20	10	3.1	\$ 109,426
IES	0.5	50	10	3.1	\$ 109,048
IES	1	2	9	3.6	\$ 104,713
IES	1	5	9	3.6	\$ 104,397
IES	1	10	9	3.2	\$ 101,116
IES	1	20	9	3.3	\$ 102,319
IES	1	50	9	3.2	\$ 101,703
CES	0.1	2	10	3.3	\$ 110,903
CES	0.1	5	10	3.2	\$ 109,517
CES	0.1	10	10	3.1	\$ 108,716
CES	0.1	20	9	3.9	\$ 107,337
CES	0.1	50	10	2.9	\$ 108,168
CES	0.2	2	9	4	\$ 107,912
CES	0.2	5	9	3.8	\$ 106,567
CES	0.2	10	9	3.8	\$ 106,584
CES	0.2	20	10	2.7	\$ 106,067
CES	0.2	50	10	2.8	\$ 106,519
CES	0.5	2	9	3	\$ 99,974
CES	0.5	5	9	3.1	\$ 100,314
CES	0.5	10	9	2.8	\$ 98,411
CES	0.5	20	9	2.8	\$ 97,917
CES	0.5	50	9	2.8	\$ 98,352
CES	1	2	9	2.4	\$ 95,317
CES	1	5	9	2.3	\$ 94,110
CES	1	10	9	2.1	\$ 92,611
CES	1	20	9	2.1	\$ 92,814
CES	1	50	9	2.1	\$ 92,739

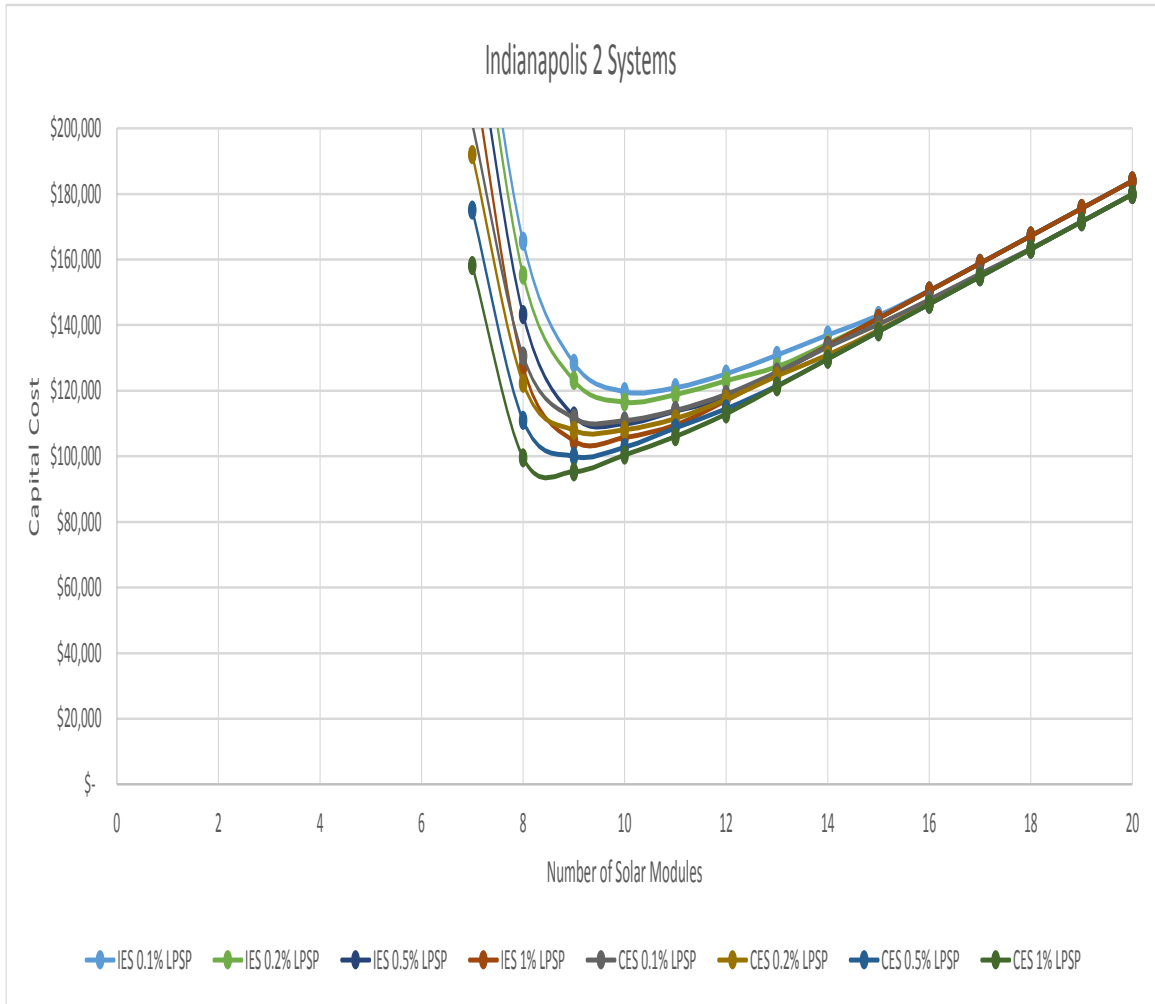


Figure 4.18. Results for varying LPSP required given June, 10% initial charge, 2 systems, and Indianapolis

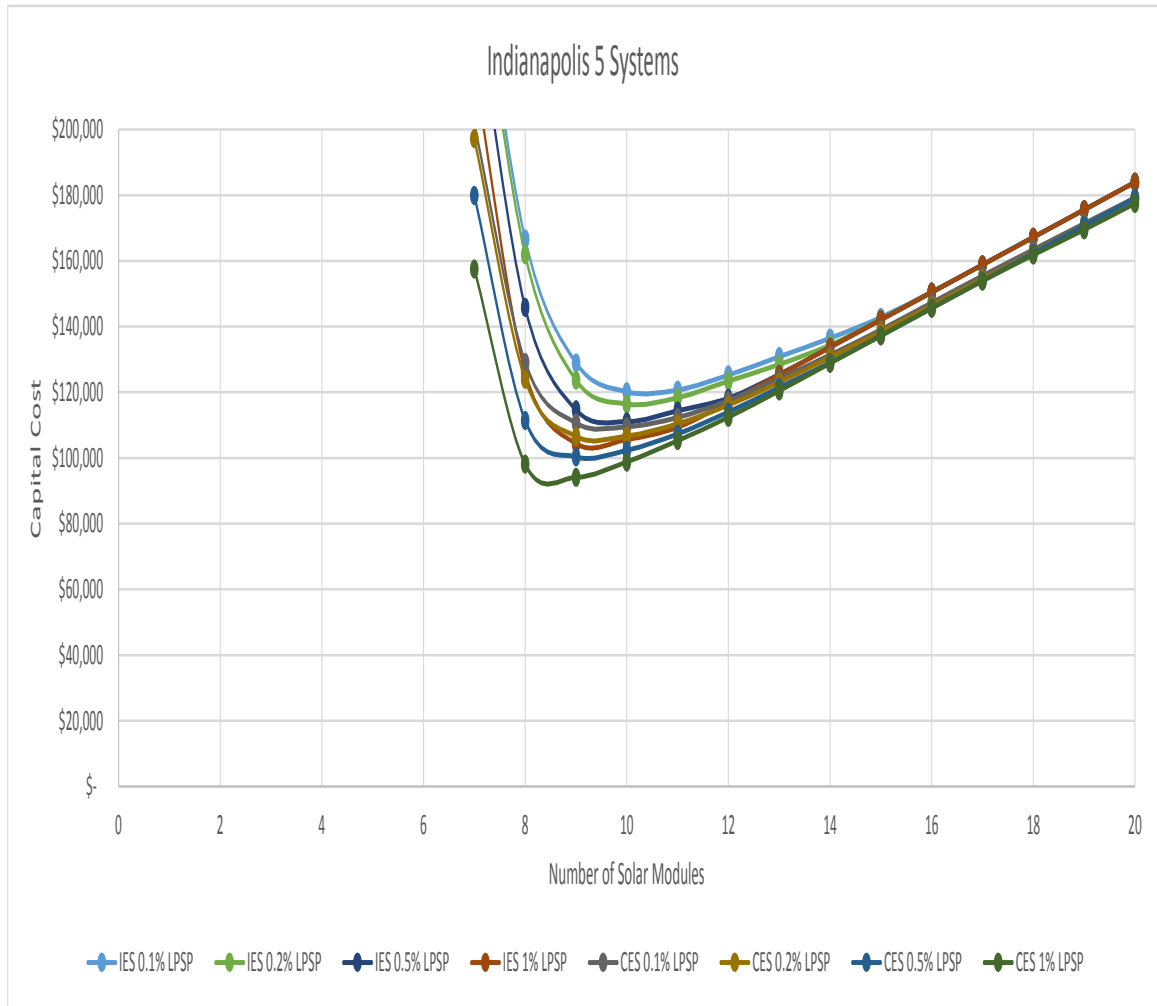


Figure 4.19. Results for varying LPSP required given June, 10% initial charge, 5 systems, and Indianapolis

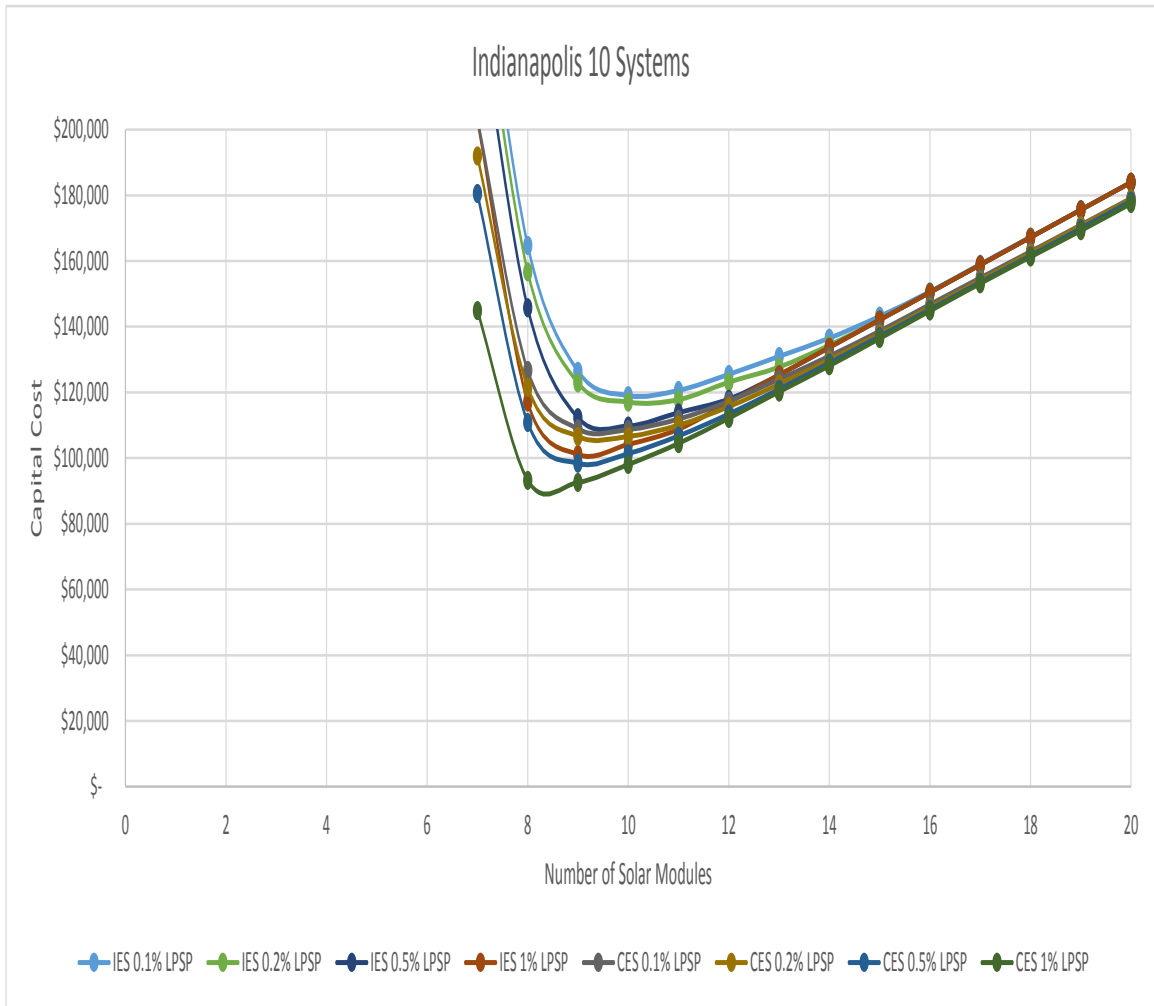


Figure 4.20. Results for varying LPSP required given June, 10% initial charge, 10 systems, and Indianapolis

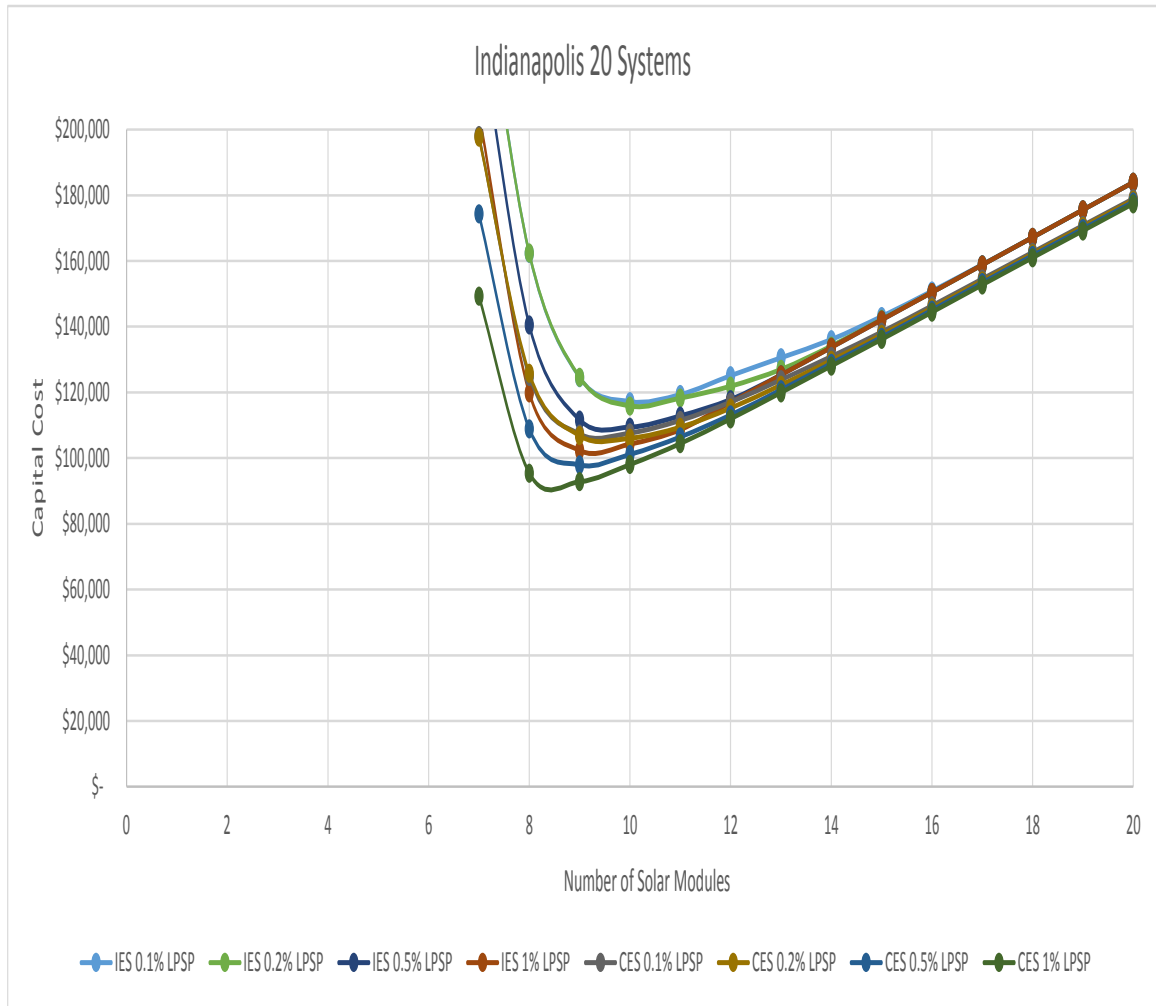


Figure 4.21. Results for varying LPSP required given June, 10% initial charge, 20 systems, and Indianapolis

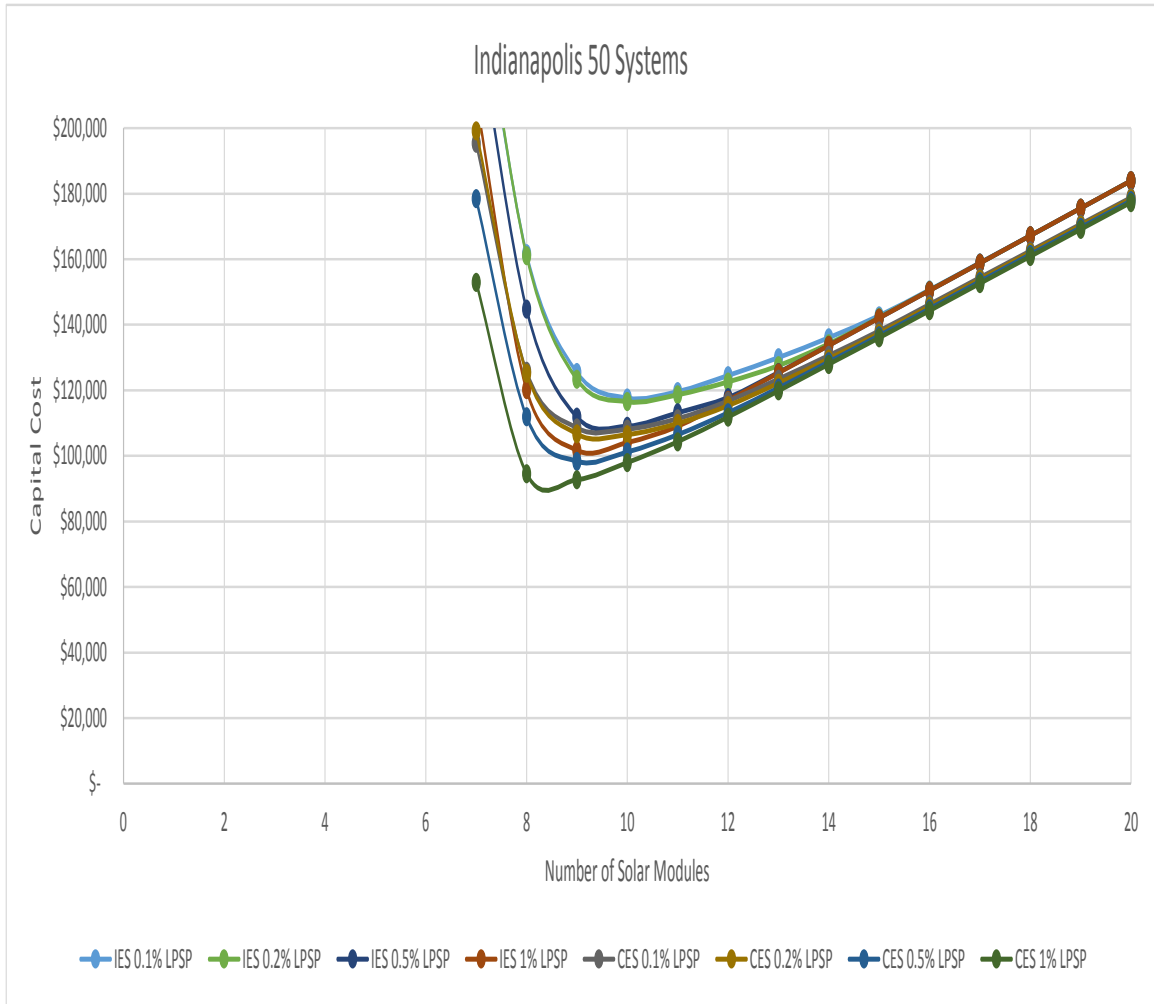


Figure 4.22. Results for varying LPSP required given June, 10% initial charge, 50 systems, and Indianapolis

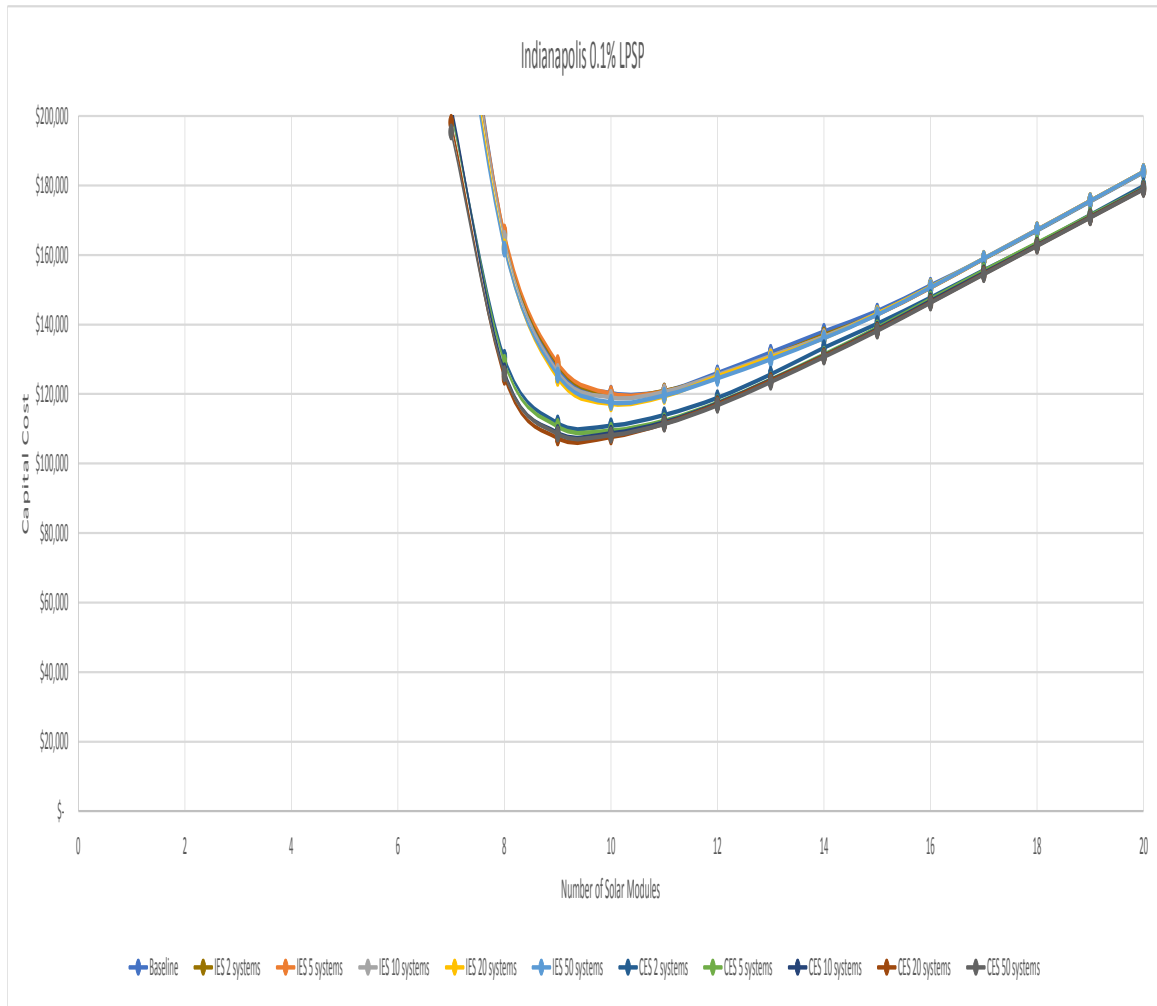


Figure 4.23. Results for varying number of systems given 0.1% LPSP required, June, 10% initial charge, and Indianapolis

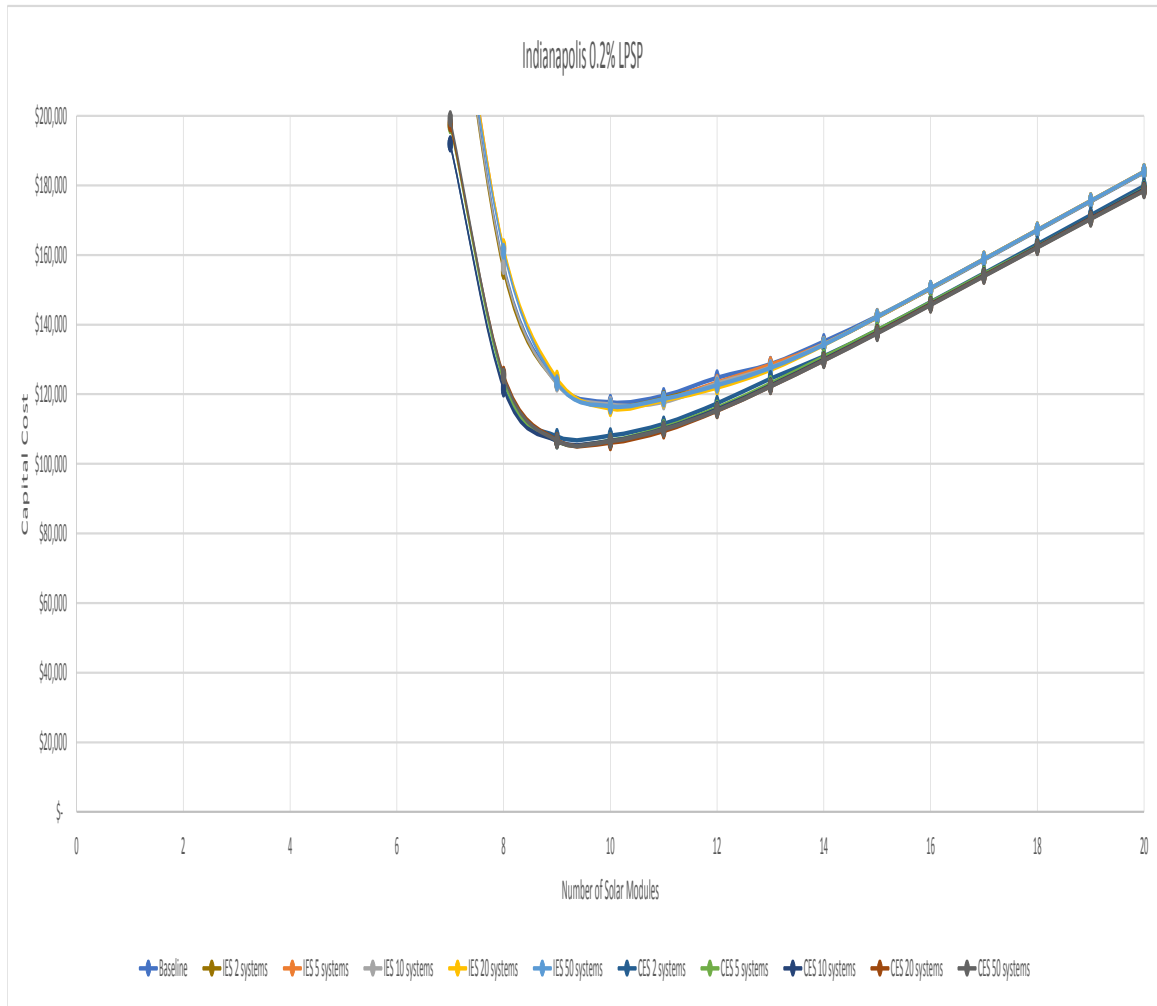


Figure 4.24. Results for varying number of systems given 0.2% LPSP required, June, 10% initial charge, and Indianapolis

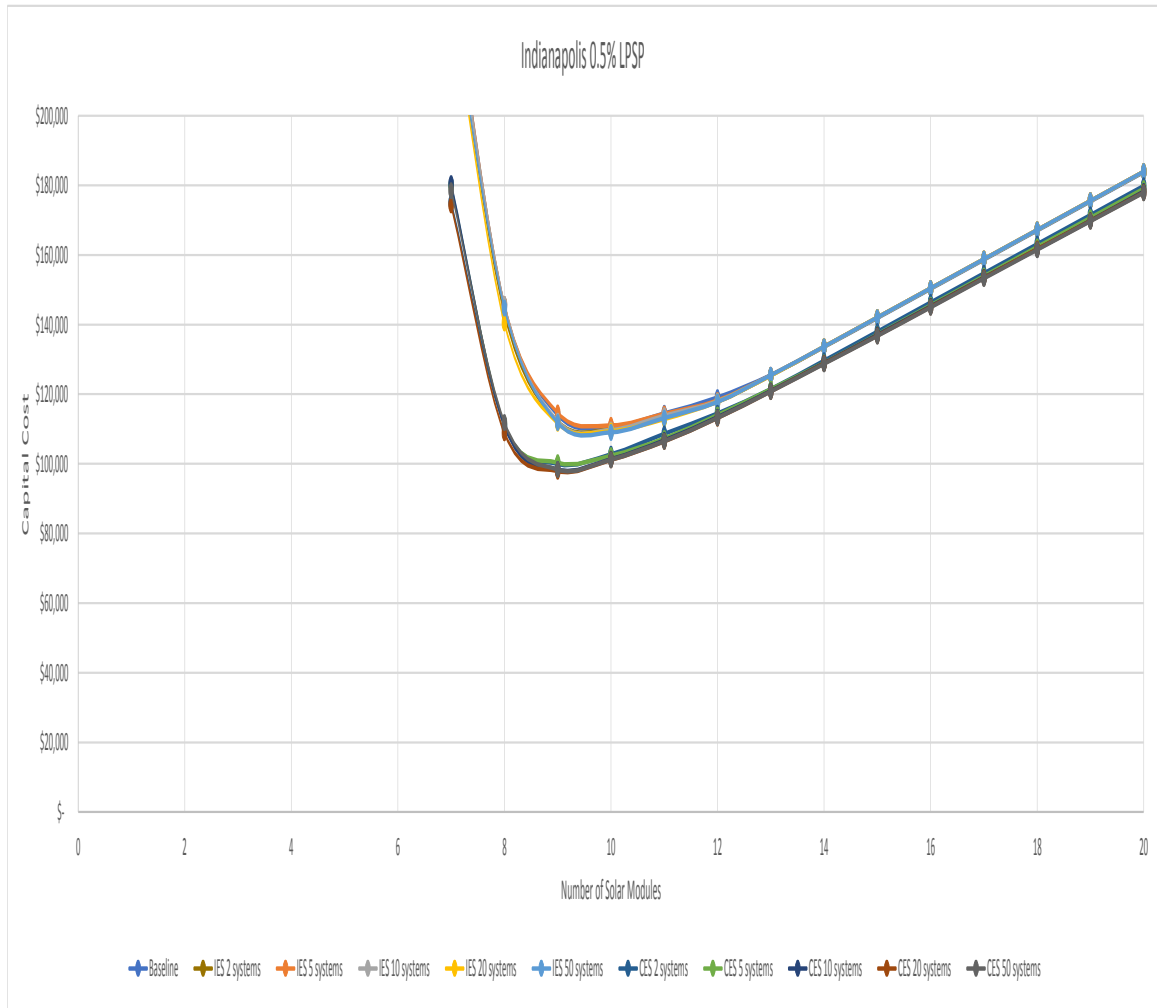


Figure 4.25. Results for varying number of systems given 0.5% LPSP required, June, 10% initial charge, and Indianapolis

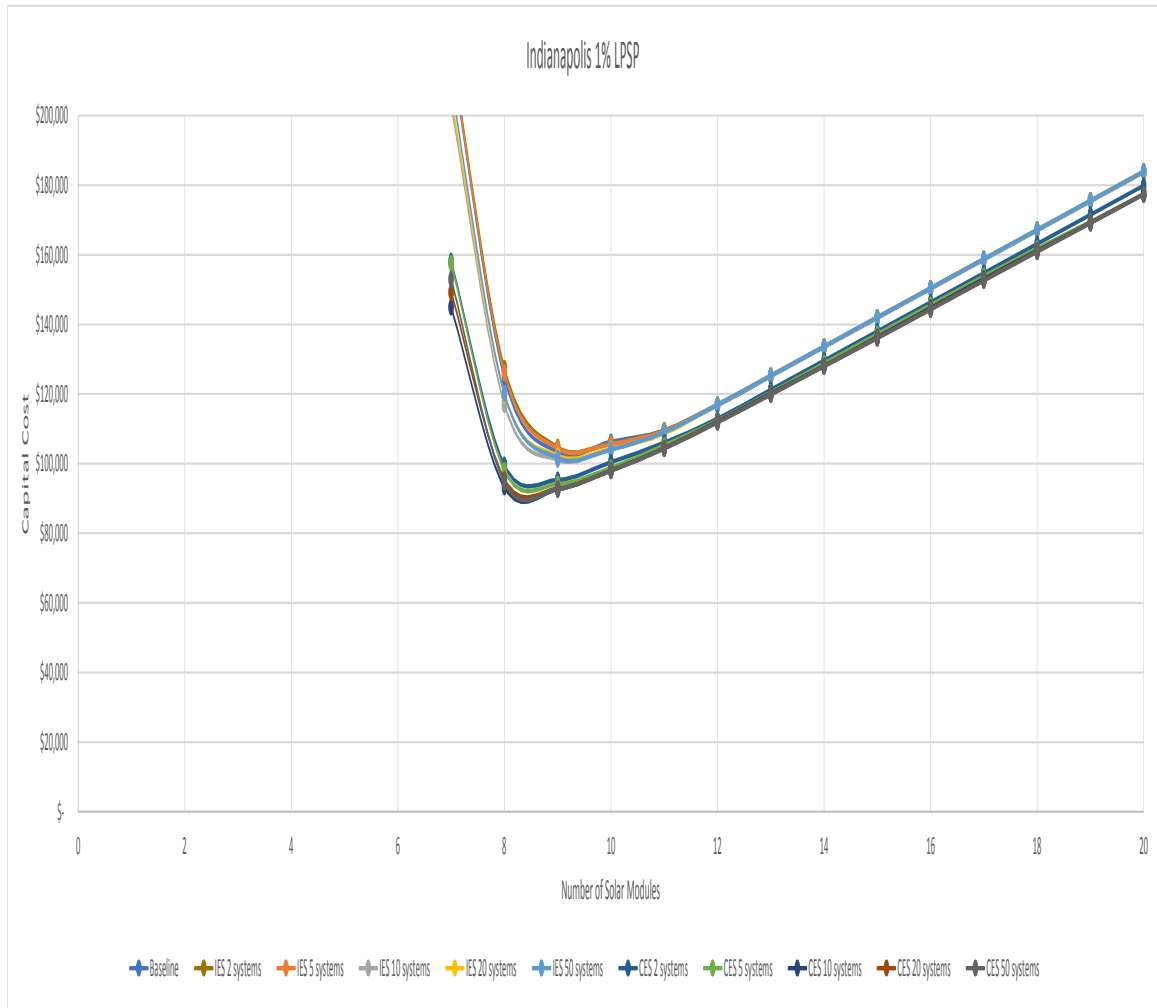


Figure 4.26. Results for varying number of systems given 1% LPSP required, June, 10% initial charge, and Indianapolis

4.4.5 Erie

This section contains all case studies for the location of Erie (Figures 4.27 - 4.35) with a corresponding summary table (Table 4.2). Erie has a climate zone of 'Cold' and a global normal irradiance of 3.0 - 3.5 kWh/sq.m/day. Erie had the highest total cost out of the geographic locations studied.

Table 4.2. Summary Table for Erie showing the optimum configurations for each case from the Main Simulation.

Summary Table for Erie					
Operating Strategy	LPSP (%)	# of Systems	Optimum # of Solar Panels	# of Batteries (Average)	Capital Cost (Average)
Baseline	0.1	-	13	3	\$ 133,282
Baseline	0.2	-	13	2.7	\$ 131,014
Baseline	0.5	-	12	3	\$ 125,148
Baseline	1	-	12	2.3	\$ 118,911
IES	0.1	2	13	3	\$ 133,037
IES	0.1	5	13	3	\$ 132,980
IES	0.1	10	13	2.9	\$ 132,696
IES	0.1	20	13	2.9	\$ 132,283
IES	0.1	50	13	2.8	\$ 131,800
IES	0.2	2	13	2.5	\$ 129,149
IES	0.2	5	13	2.5	\$ 129,675
IES	0.2	10	13	2.5	\$ 129,132
IES	0.2	20	13	2.4	\$ 128,496
IES	0.2	50	13	2.5	\$ 128,965
IES	0.5	2	12	2.8	\$ 123,688
IES	0.5	5	12	2.8	\$ 123,534
IES	0.5	10	12	2.8	\$ 123,582
IES	0.5	20	12	2.8	\$ 123,594
IES	0.5	50	12	2.7	\$ 122,719
IES	1	2	12	2.1	\$ 117,815
IES	1	5	12	2.1	\$ 117,766
IES	1	10	12	2	\$ 117,621
IES	1	20	12	2.1	\$ 117,702
IES	1	50	12	2	\$ 117,204
CES	0.1	2	12	2.8	\$ 123,526
CES	0.1	5	12	2.6	\$ 121,719
CES	0.1	10	12	2.6	\$ 121,800
CES	0.1	20	12	2.5	\$ 121,010
CES	0.1	50	12	2.4	\$ 120,540
CES	0.2	2	12	2.4	\$ 120,083
CES	0.2	5	12	2.2	\$ 118,933
CES	0.2	10	12	2.2	\$ 118,641
CES	0.2	20	12	2.1	\$ 118,026
CES	0.2	50	12	2.2	\$ 118,312
CES	0.5	2	12	2.2	\$ 117,167
CES	0.5	5	12	1.8	\$ 115,320
CES	0.5	10	12	1.8	\$ 114,972
CES	0.5	20	12	1.8	\$ 115,025
CES	0.5	50	12	1.7	\$ 114,688
CES	1	2	11	2.2	\$ 110,289
CES	1	5	11	2	\$ 108,822
CES	1	10	11	2	\$ 108,345
CES	1	20	11	2	\$ 108,644
CES	1	50	11	1.9	\$ 108,048

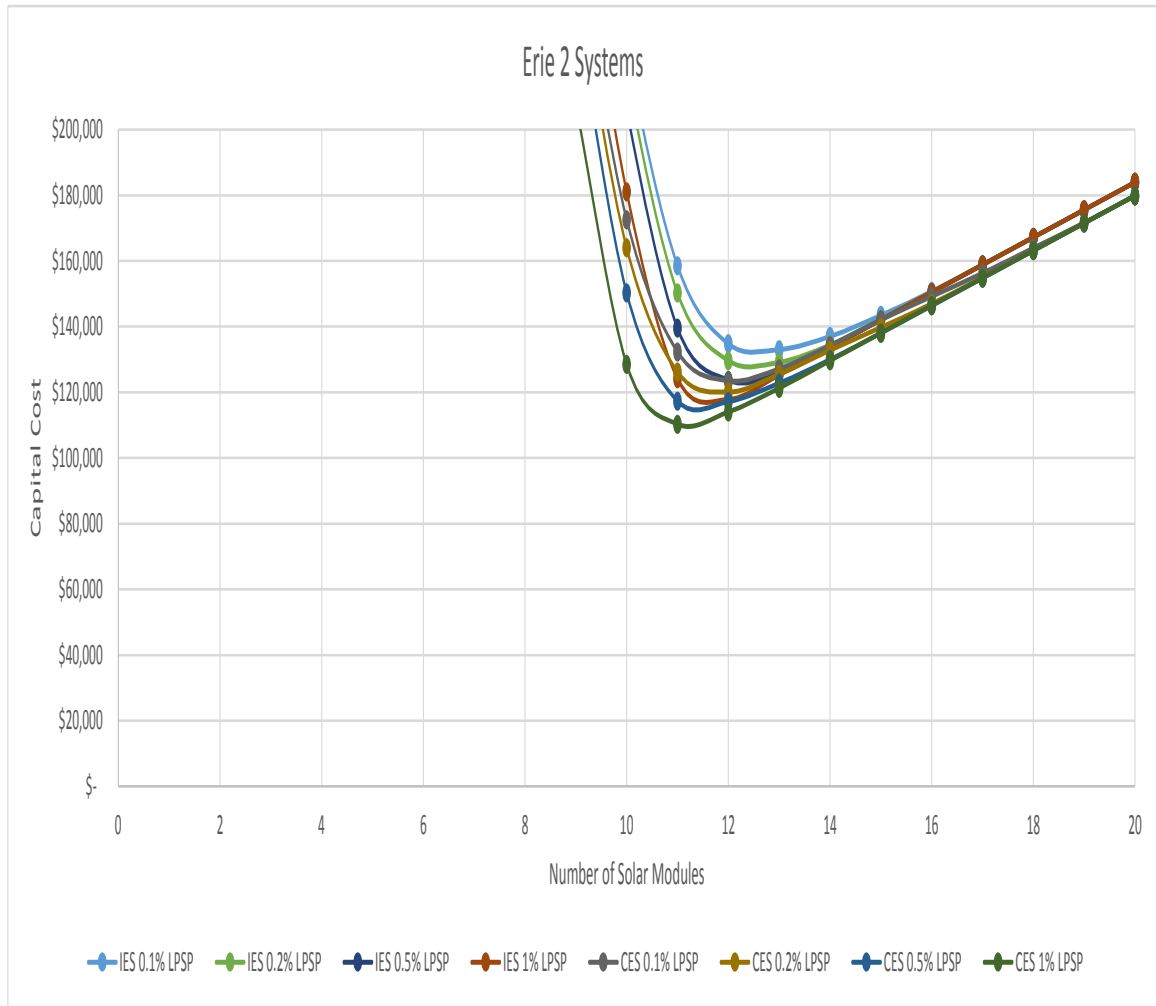


Figure 4.27. Results for varying LPSP required given June, 10% initial charge, 2 systems, and Erie

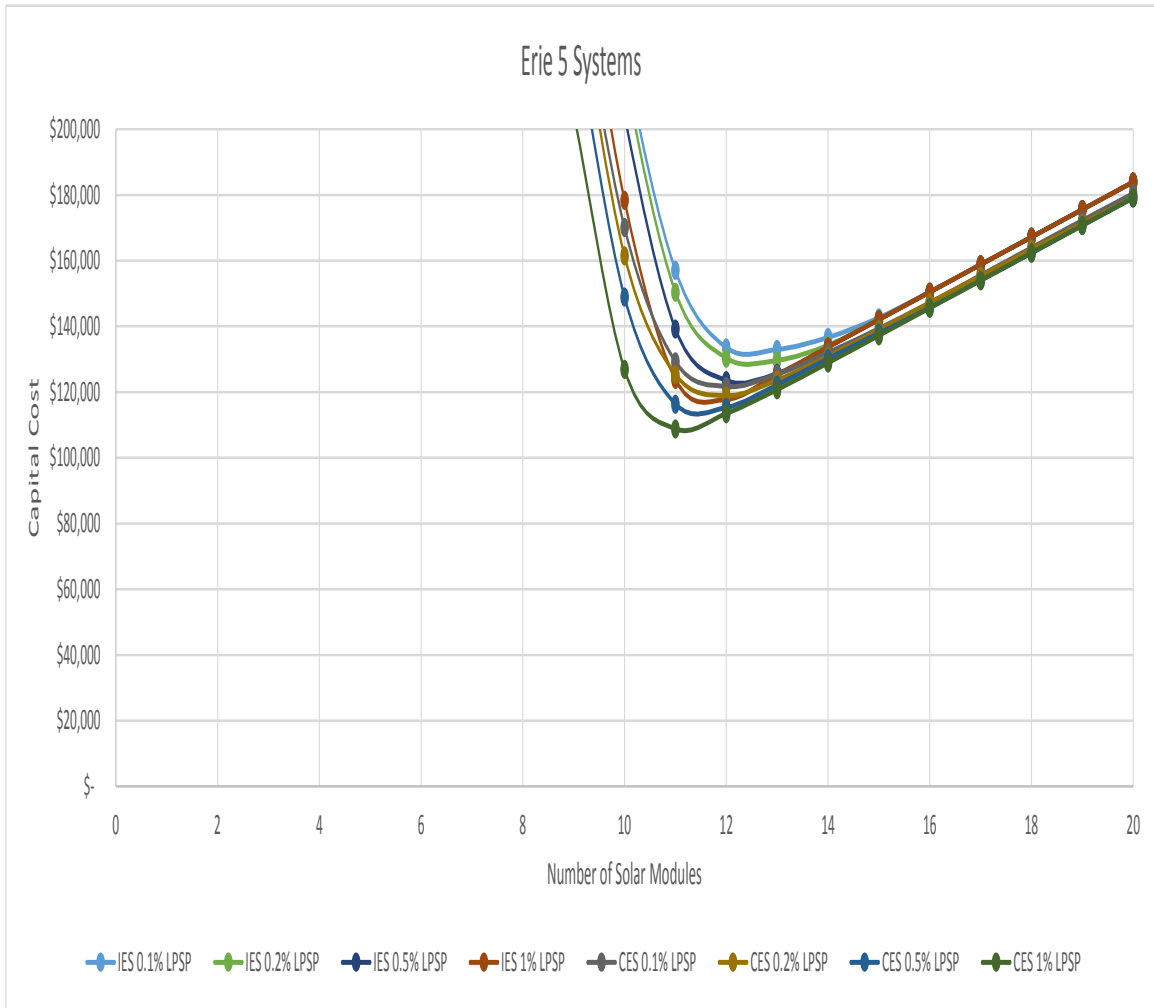


Figure 4.28. Results for varying LPSP required given June, 10% initial charge, 5 systems, and Erie

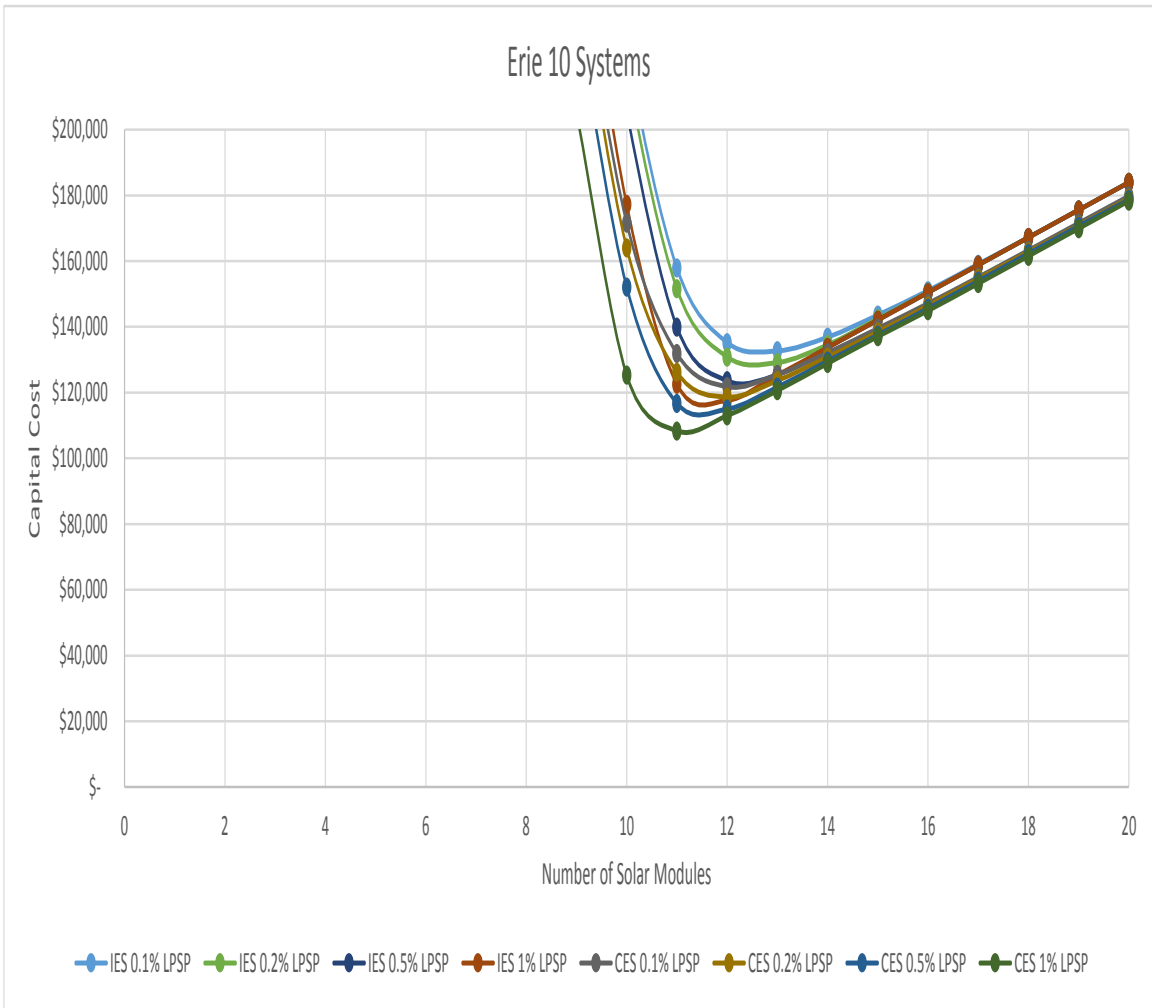


Figure 4.29. Results for varying LPSP required given June, 10% initial charge, 10 systems, and Erie

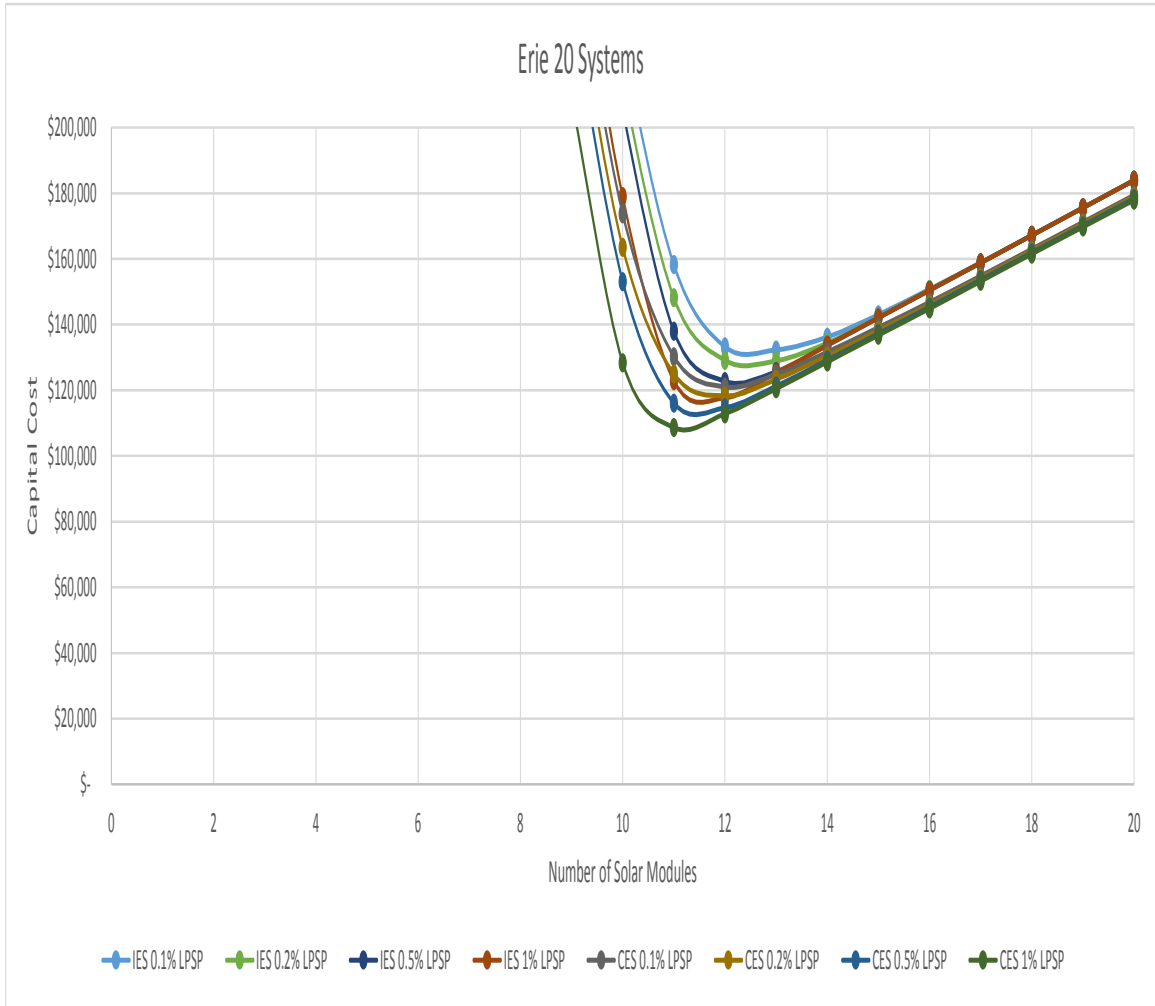


Figure 4.30. Results for varying LPSP required given June, 10% initial charge, 20 systems, and Erie

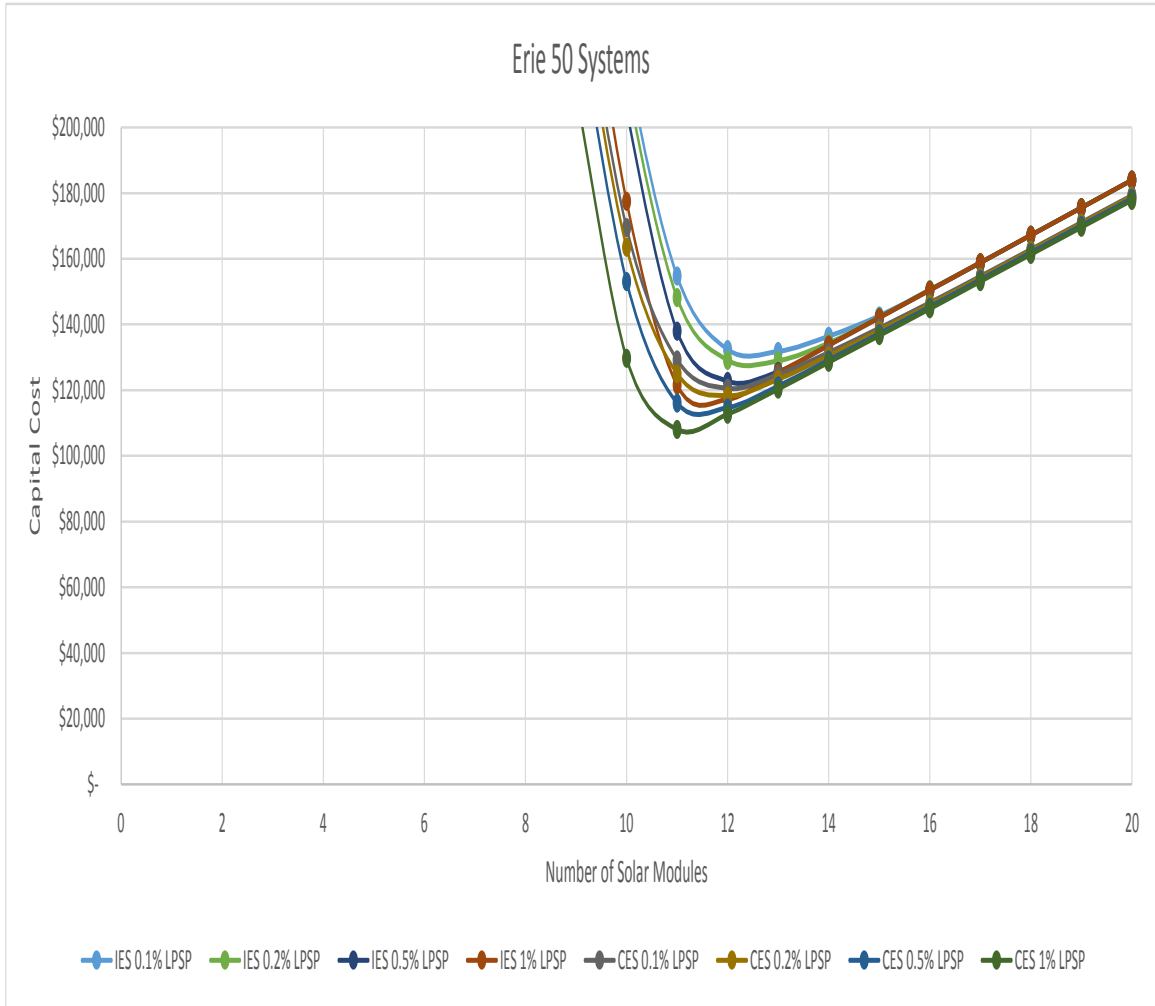


Figure 4.31. Results for varying LPSP required given June, 10% initial charge, 50 systems, and Erie

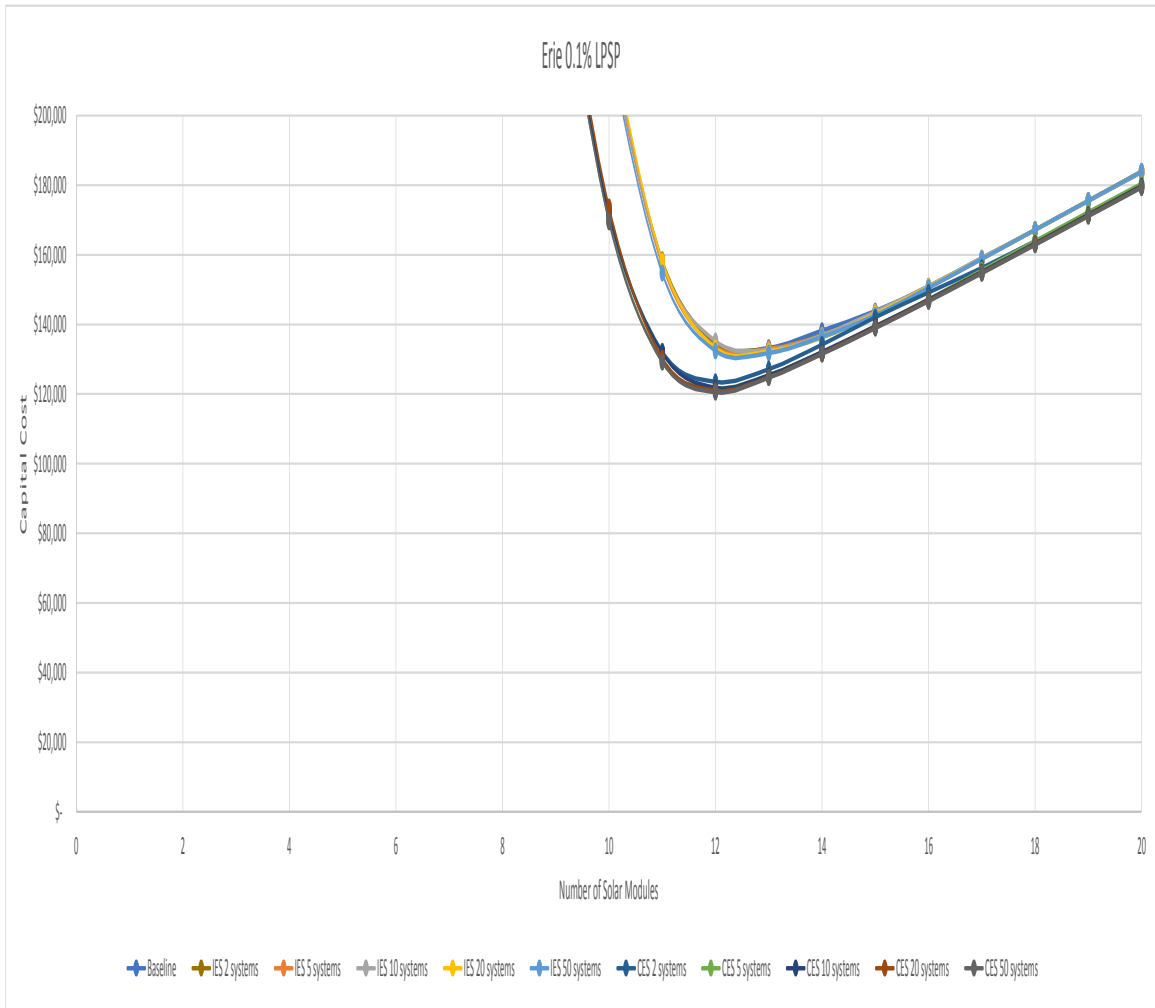


Figure 4.32. Results for varying number of systems given 0.1% LPSP required, June, 10% initial charge, and Erie

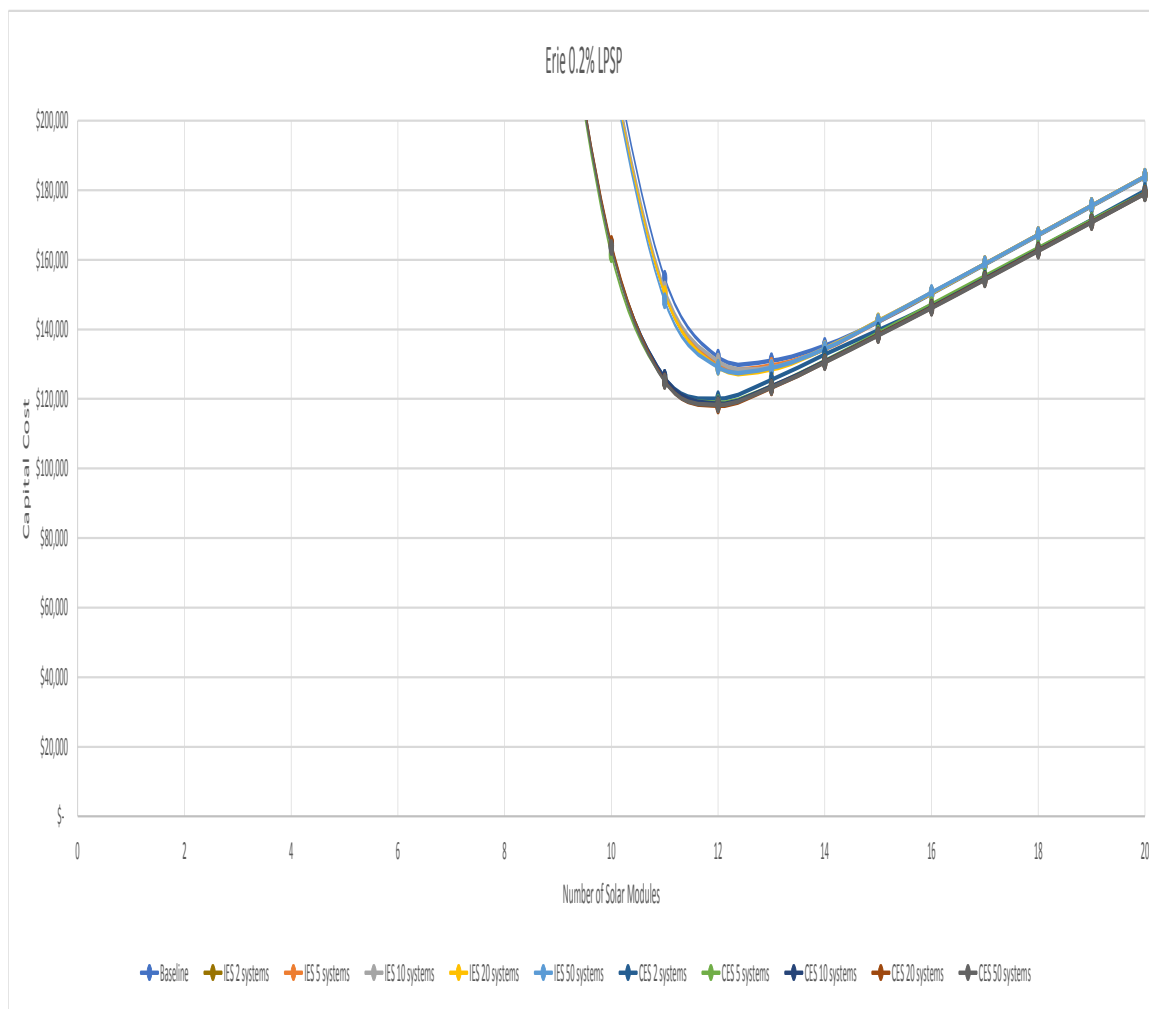


Figure 4.33. Results for varying number of systems given 0.2% LPSP required, June, 10% initial charge, and Erie

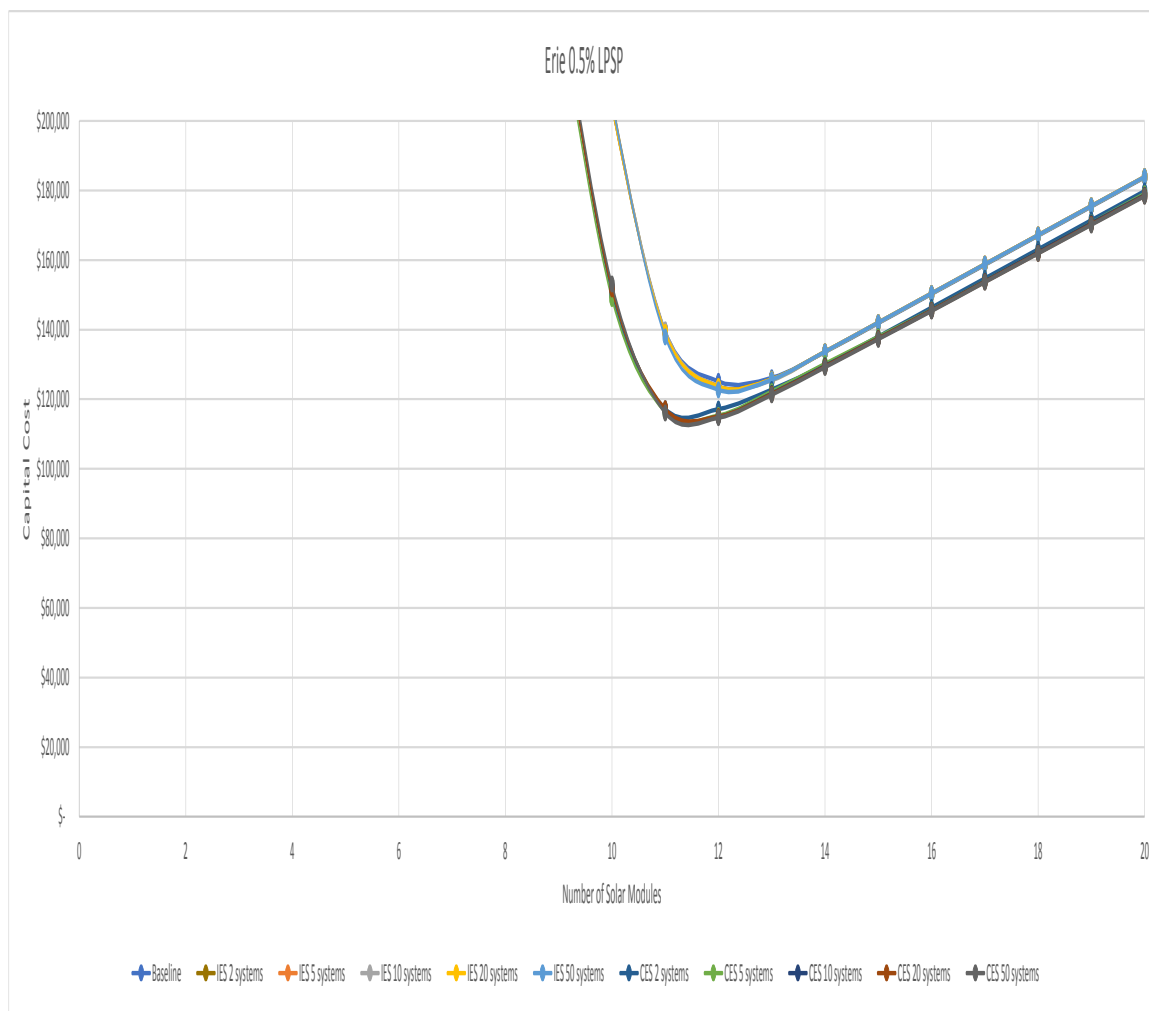


Figure 4.34. Results for varying number of systems given 0.5% LPSP required, June, 10% initial charge, and Erie

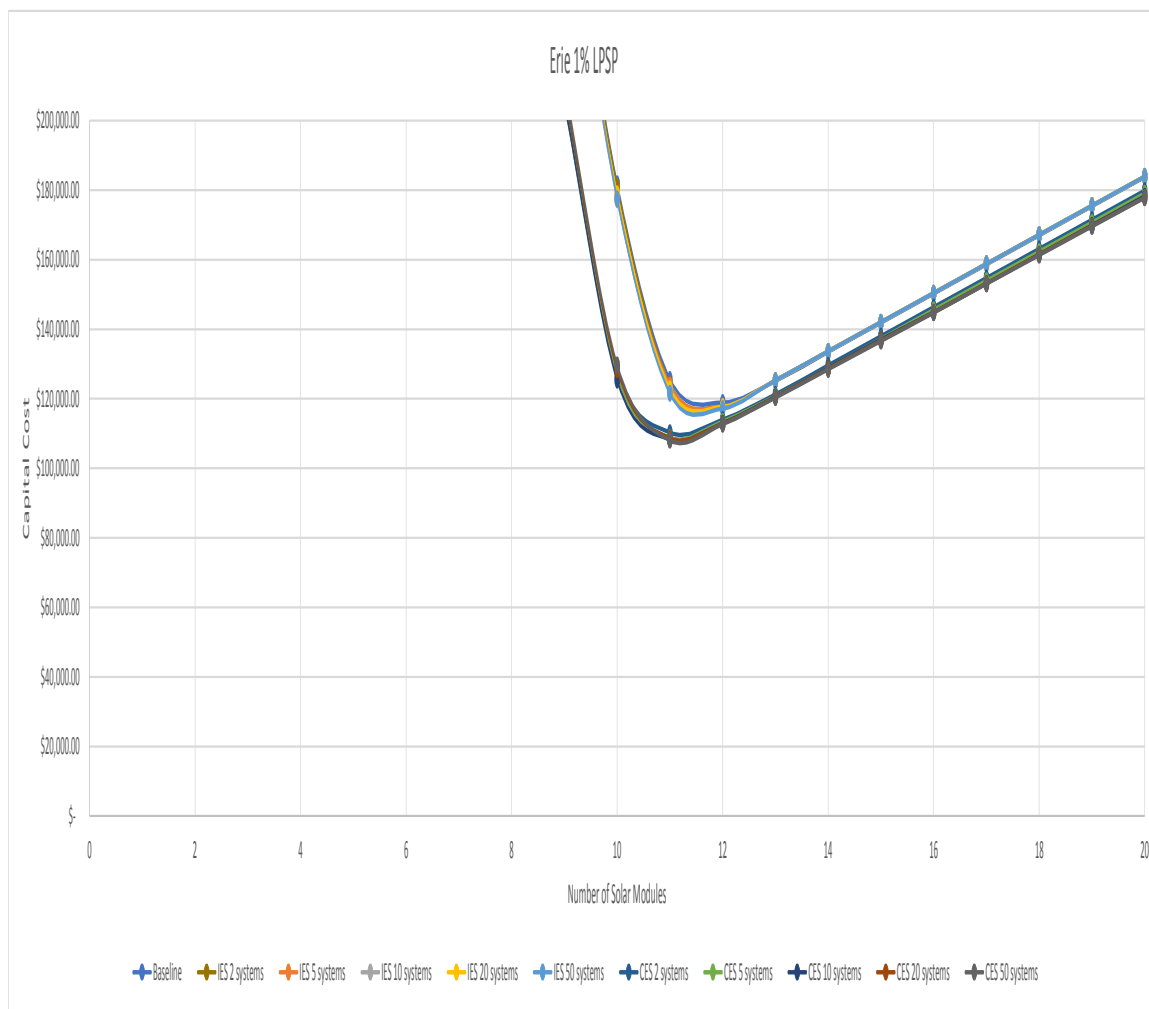


Figure 4.35. Results for varying number of systems given 1% LPSP required, June, 10% initial charge, and Erie

4.4.6 Phoenix

This section contains all case studies for the location of Phoenix (Figures 4.36 - 4.44) with a corresponding summary table (Table 4.3). Phoenix has a climate zone of 'Hot-Dry / Mixed-Dry' and a global normal irradiance of 5.0 - 5.5 kWh/sq.m/day. Phoenix had the lowest average cost per system out of the geographic locations studied.

Table 4.3. Summary Table for Phoenix showing the optimum configurations for each case from the Main Simulation.

Summary Table for Phoenix					
Operating Strategy	LPSP (%)	# of Systems	Optimum # of Solar Panels	# of Batteries (Average)	Capital Cost (Average)
Baseline	0.1	-	4	4	\$ 65,908
Baseline	0.2	-	4	3.8	\$ 64,126
Baseline	0.5	-	4	3.2	\$ 59,752
Baseline	1	-	4	3	\$ 57,970
IES	0.1	2	4	4.1	\$ 66,756
IES	0.1	5	4	3.8	\$ 64,358
IES	0.1	10	4	4	\$ 66,278
IES	0.1	20	4	3.8	\$ 64,666
IES	0.1	50	4	3.8	\$ 64,865
IES	0.2	2	4	3.7	\$ 63,759
IES	0.2	5	4	3.5	\$ 61,815
IES	0.2	10	4	3.5	\$ 62,074
IES	0.2	20	4	3.4	\$ 61,199
IES	0.2	50	4	3.4	\$ 61,191
IES	0.5	2	4	3.1	\$ 59,142
IES	0.5	5	4	3.1	\$ 59,093
IES	0.5	10	4	3.2	\$ 59,385
IES	0.5	20	4	3.1	\$ 58,522
IES	0.5	50	4	3.1	\$ 58,638
IES	1	2	4	2.9	\$ 57,198
IES	1	5	4	2.8	\$ 56,485
IES	1	10	4	2.8	\$ 56,550
IES	1	20	4	2.6	\$ 55,060
IES	1	50	4	2.4	\$ 53,310
CES	0.1	2	4	3.3	\$ 60,438
CES	0.1	5	4	3	\$ 58,170
CES	0.1	10	4	3.2	\$ 59,247
CES	0.1	20	4	3.1	\$ 58,429
CES	0.1	50	4	3.1	\$ 58,867
CES	0.2	2	4	2.9	\$ 57,563
CES	0.2	5	4	2.8	\$ 56,129
CES	0.2	10	4	2.7	\$ 55,870
CES	0.2	20	4	2.7	\$ 55,222
CES	0.2	50	4	2.7	\$ 55,576
CES	0.5	2	4	2.6	\$ 54,485
CES	0.5	5	4	2.4	\$ 52,856
CES	0.5	10	4	2.3	\$ 52,322
CES	0.5	20	4	2.3	\$ 51,933
CES	0.5	50	4	2.2	\$ 51,899
CES	1	2	4	2.2	\$ 51,447
CES	1	5	4	2.1	\$ 50,394
CES	1	10	4	2	\$ 49,924
CES	1	20	4	2	\$ 49,803
CES	1	50	4	2	\$ 49,649

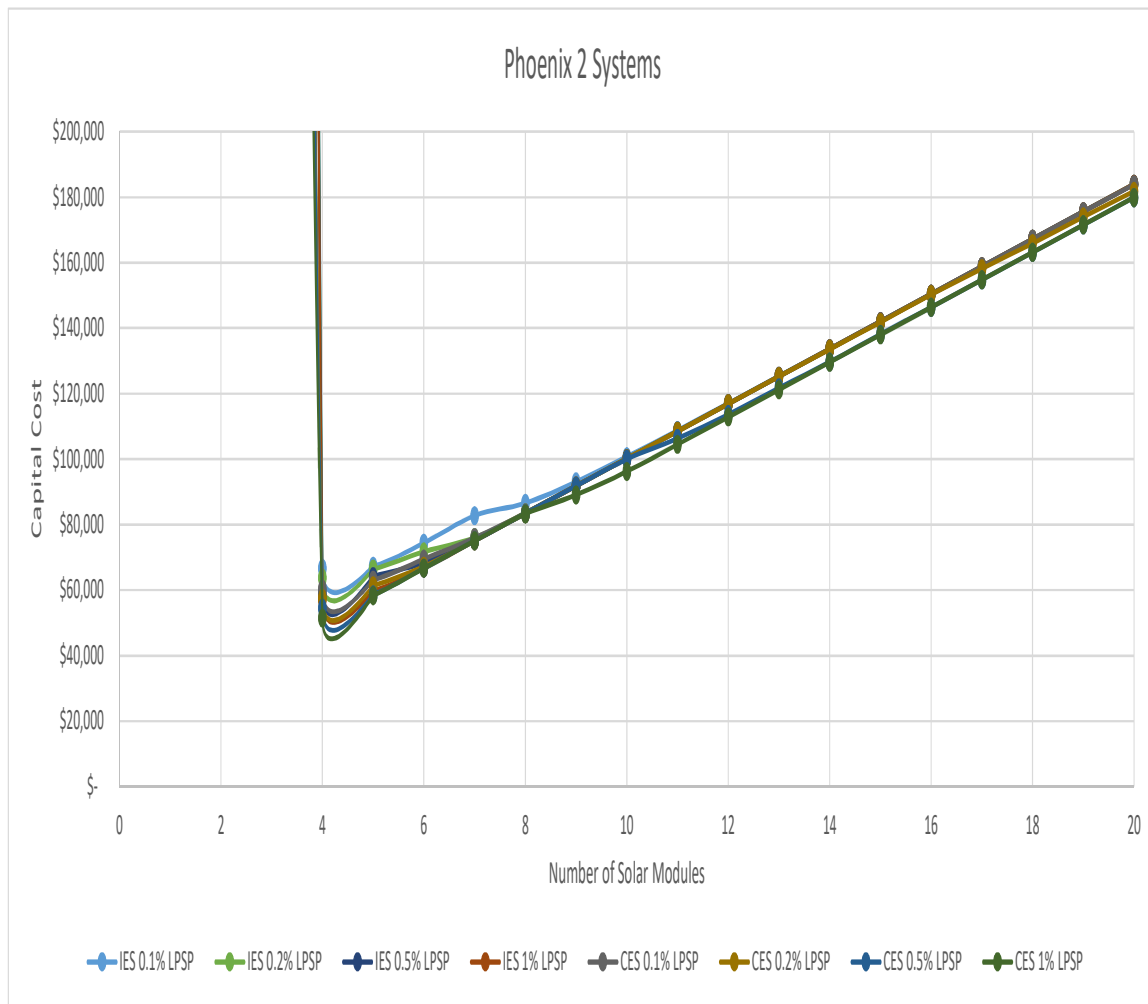


Figure 4.36. Results for varying LPSP required given June, 10% initial charge, 2 systems, and Phoenix

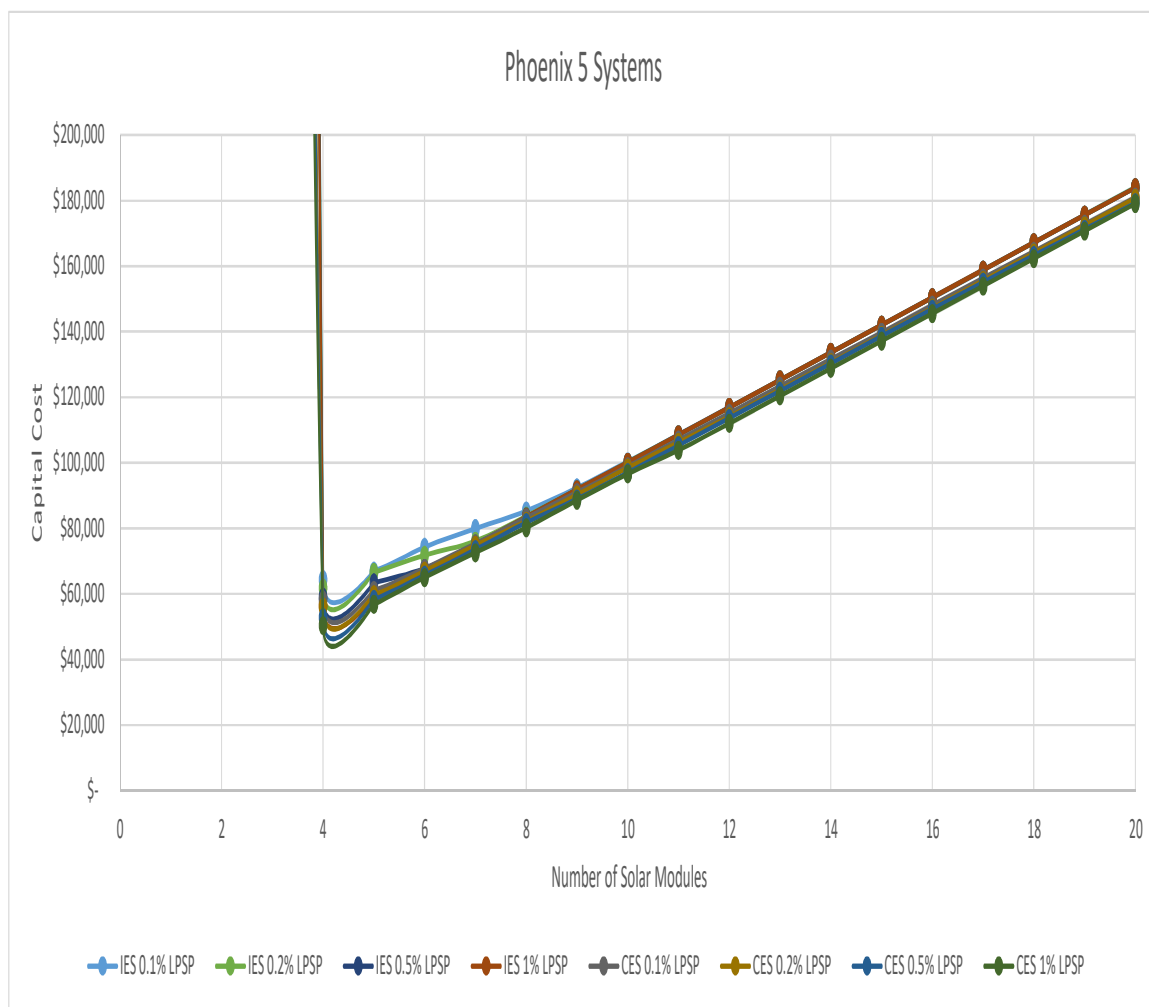


Figure 4.37. Results for varying LPSP required given June, 10% initial charge, 5 systems, and Phoenix

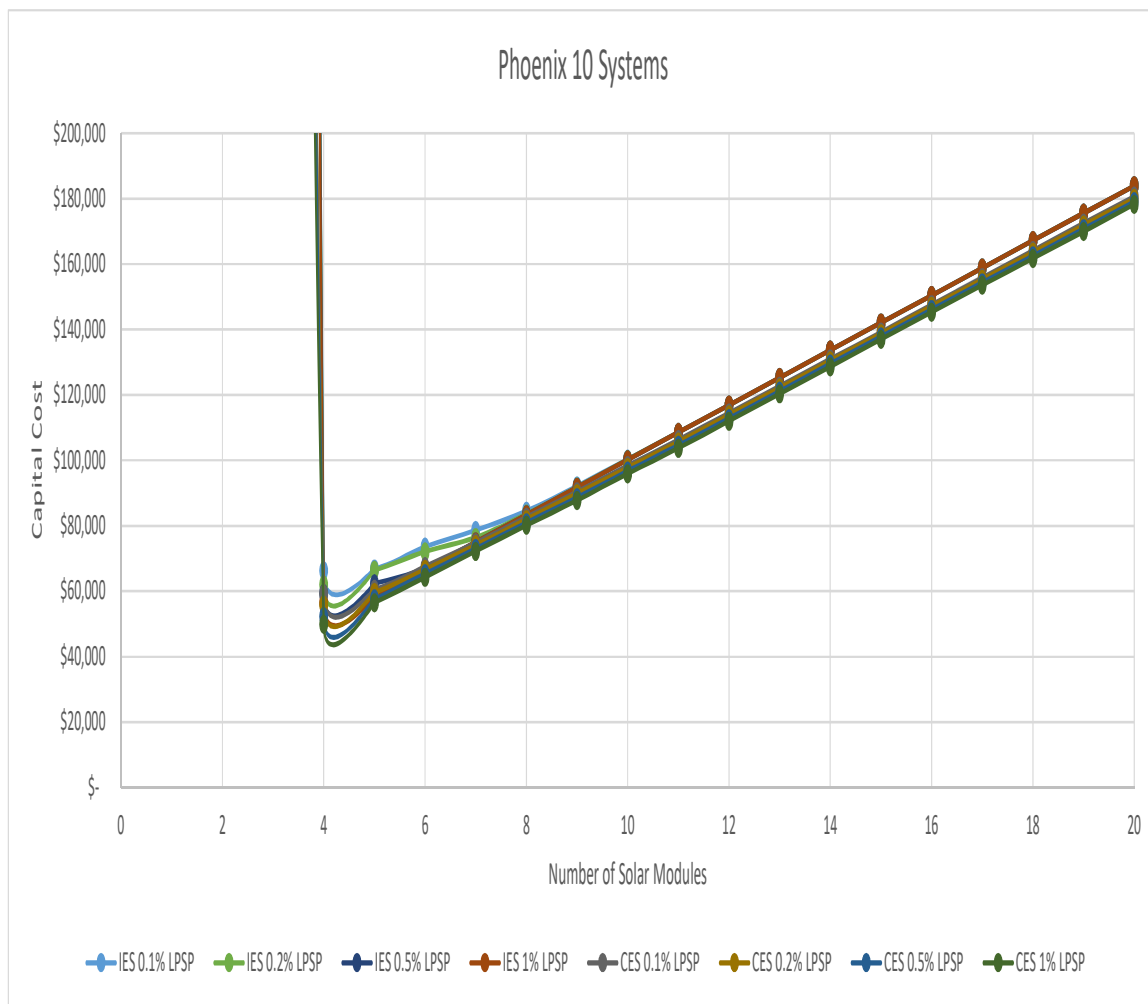


Figure 4.38. Results for varying LPSP required given June, 10% initial charge, 10 systems, and Phoenix

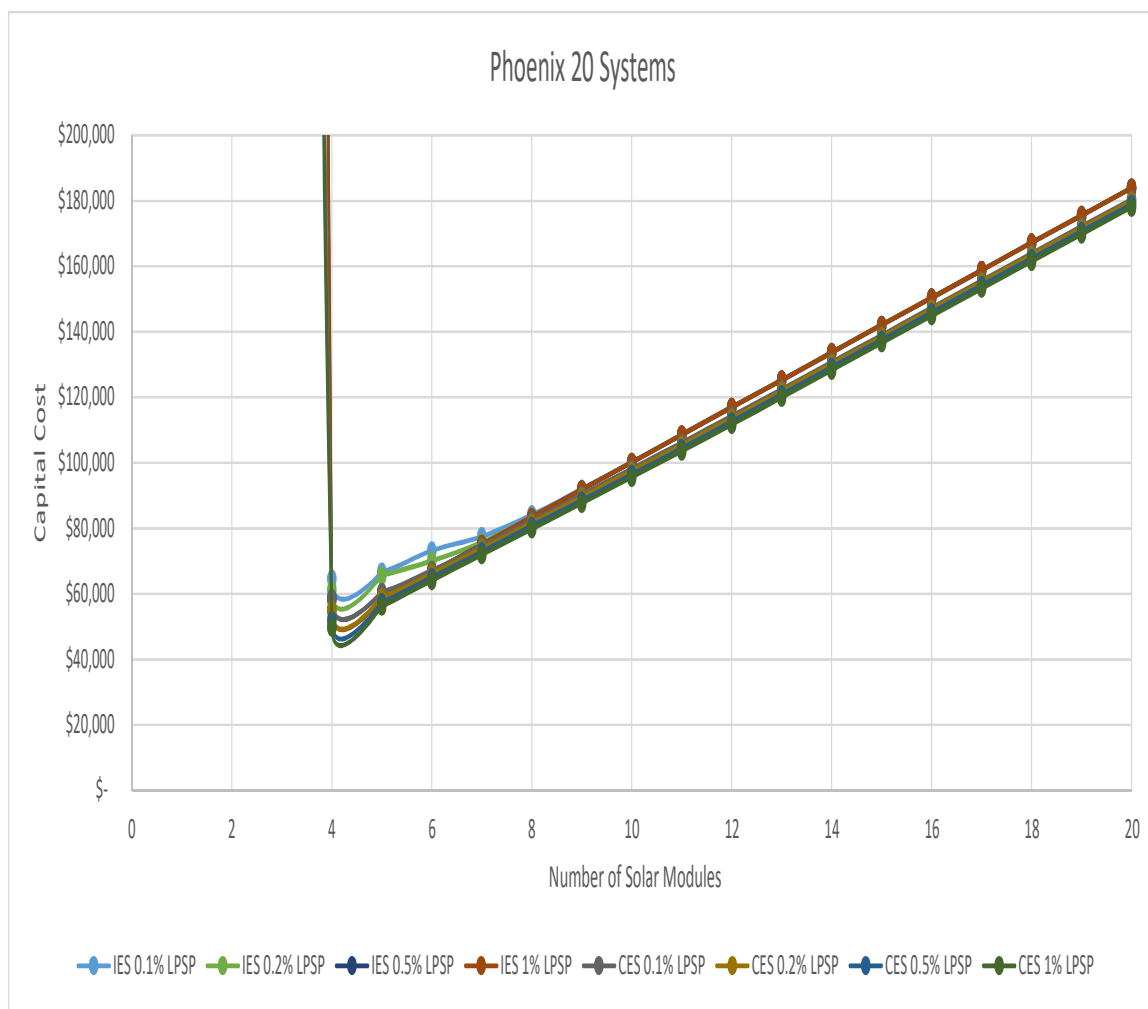


Figure 4.39. Results for varying LPSP required given June, 10% initial charge, 20 systems, and Phoenix

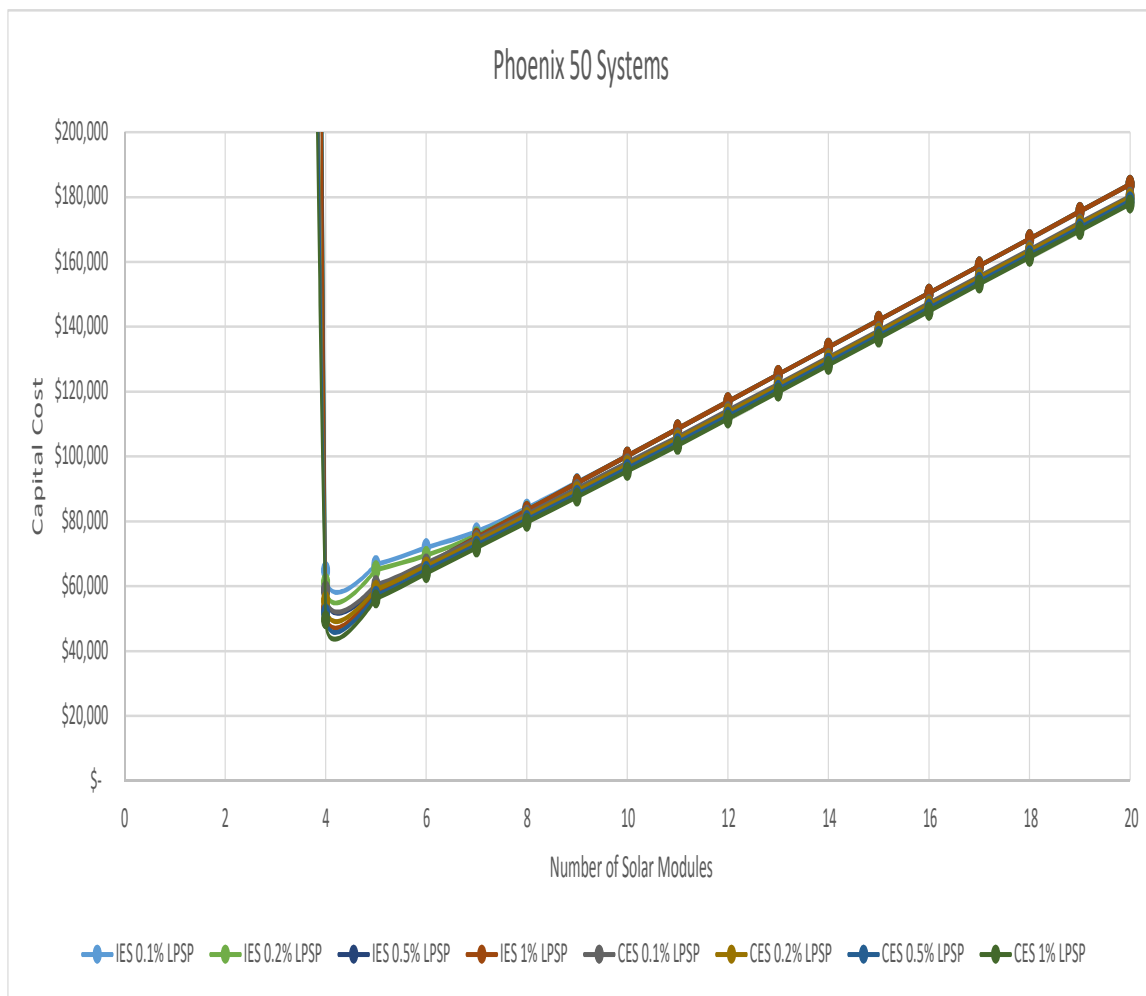


Figure 4.40. Results for varying LPSP required given June, 10% initial charge, 50 systems, and Phoenix

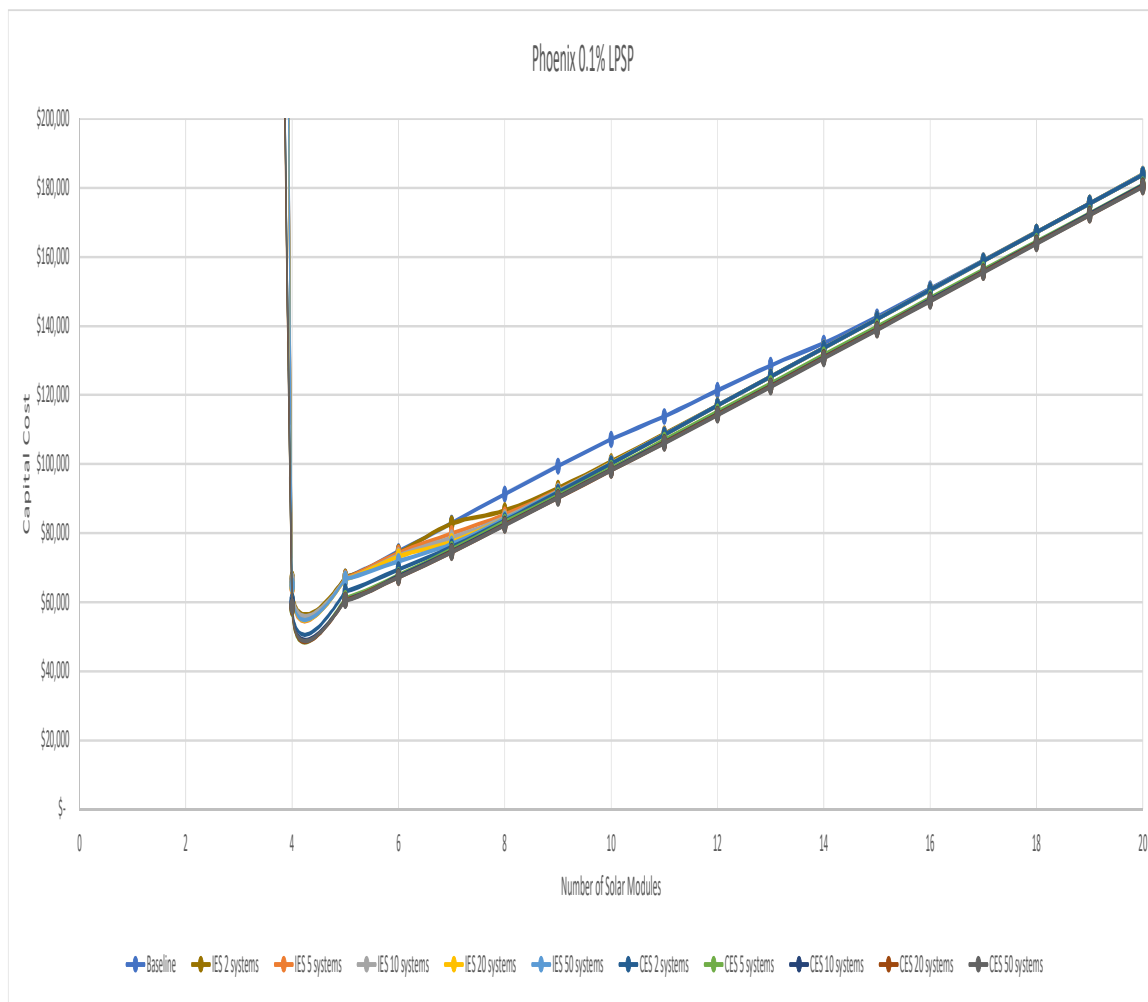


Figure 4.41. Results for varying number of systems given 0.1% LPSP required, June, 10% initial charge, and Phoenix

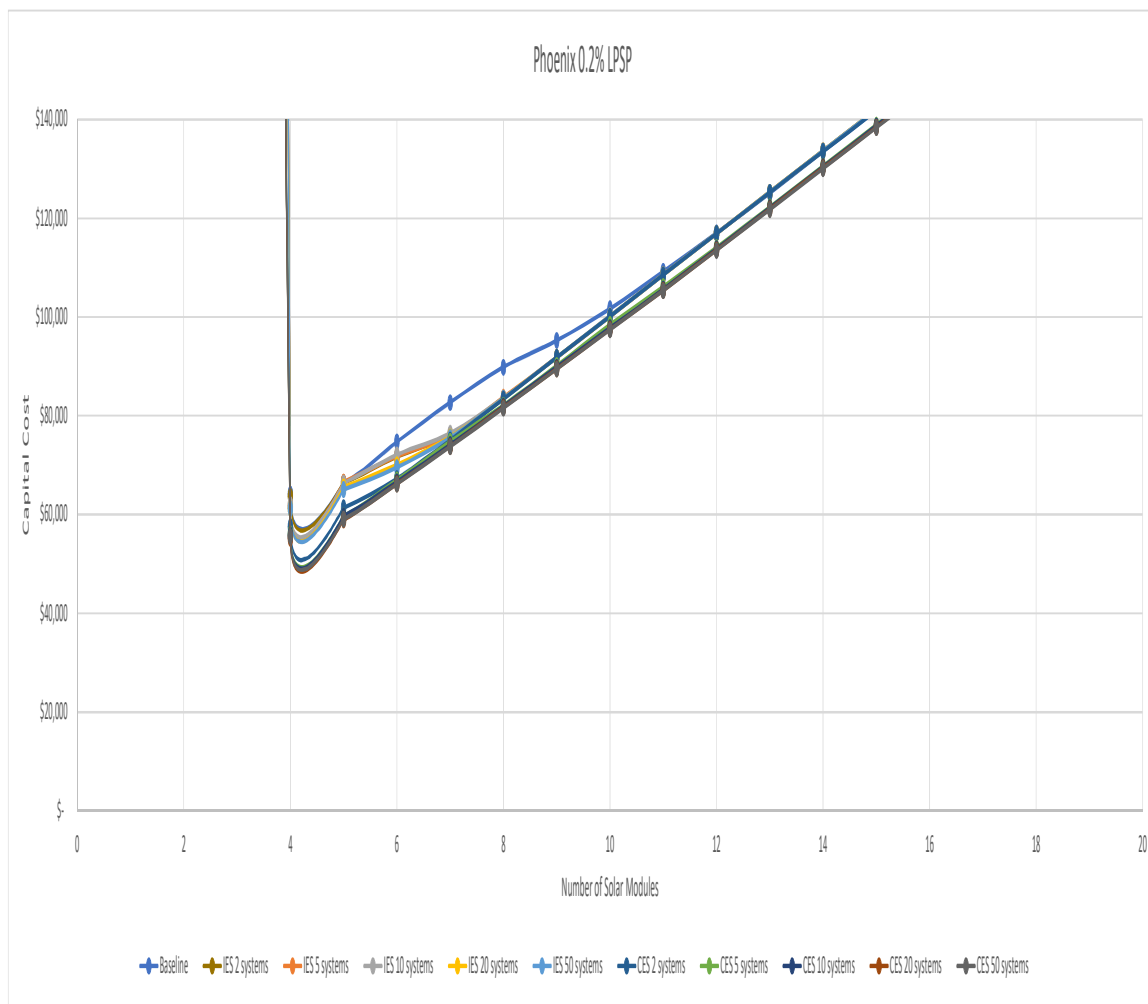


Figure 4.42. Results for varying number of systems given 0.2% LPSP required, June, 10% initial charge, and Phoenix

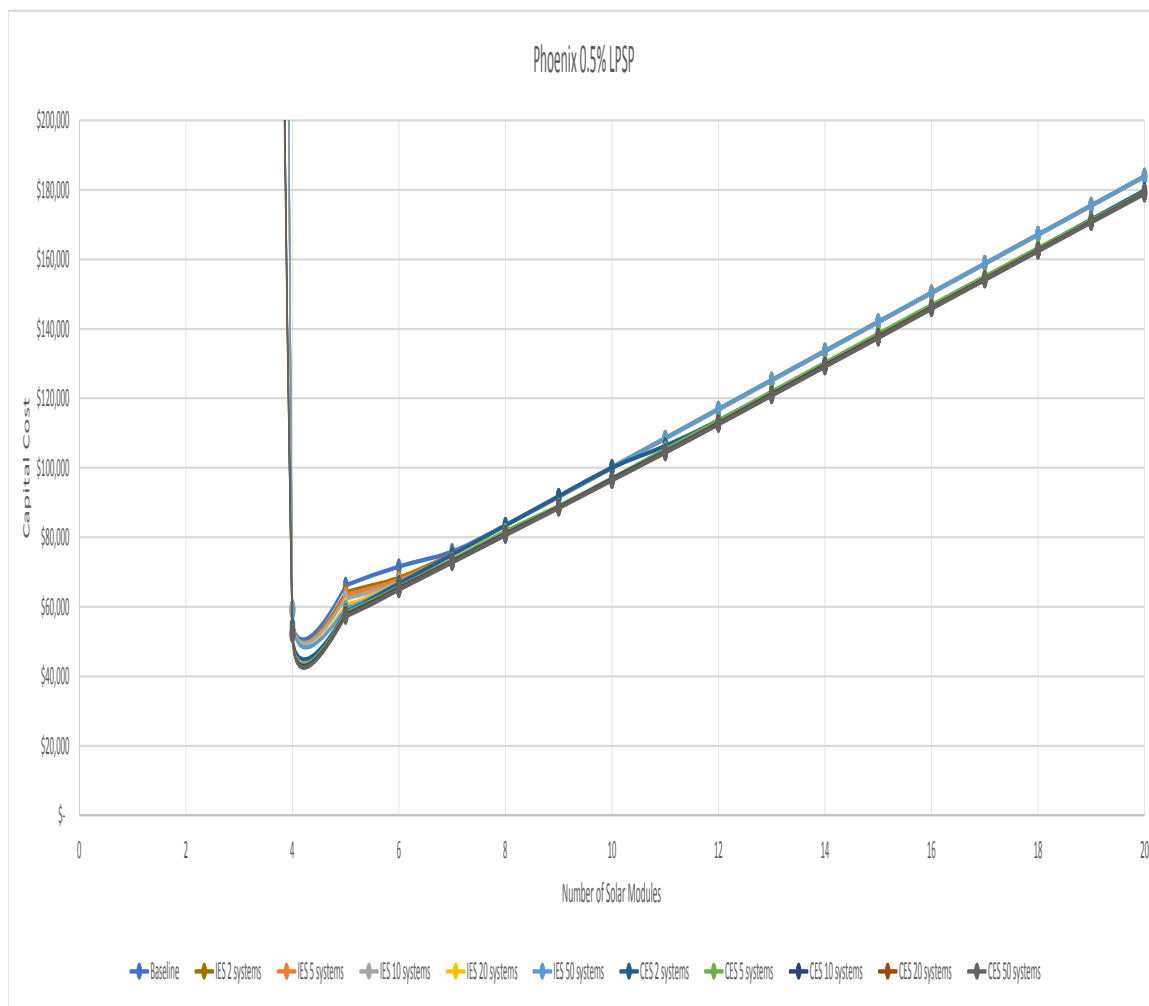


Figure 4.43. Results for varying number of systems given 0.5% LPSP required, June, 10% initial charge, and Phoenix

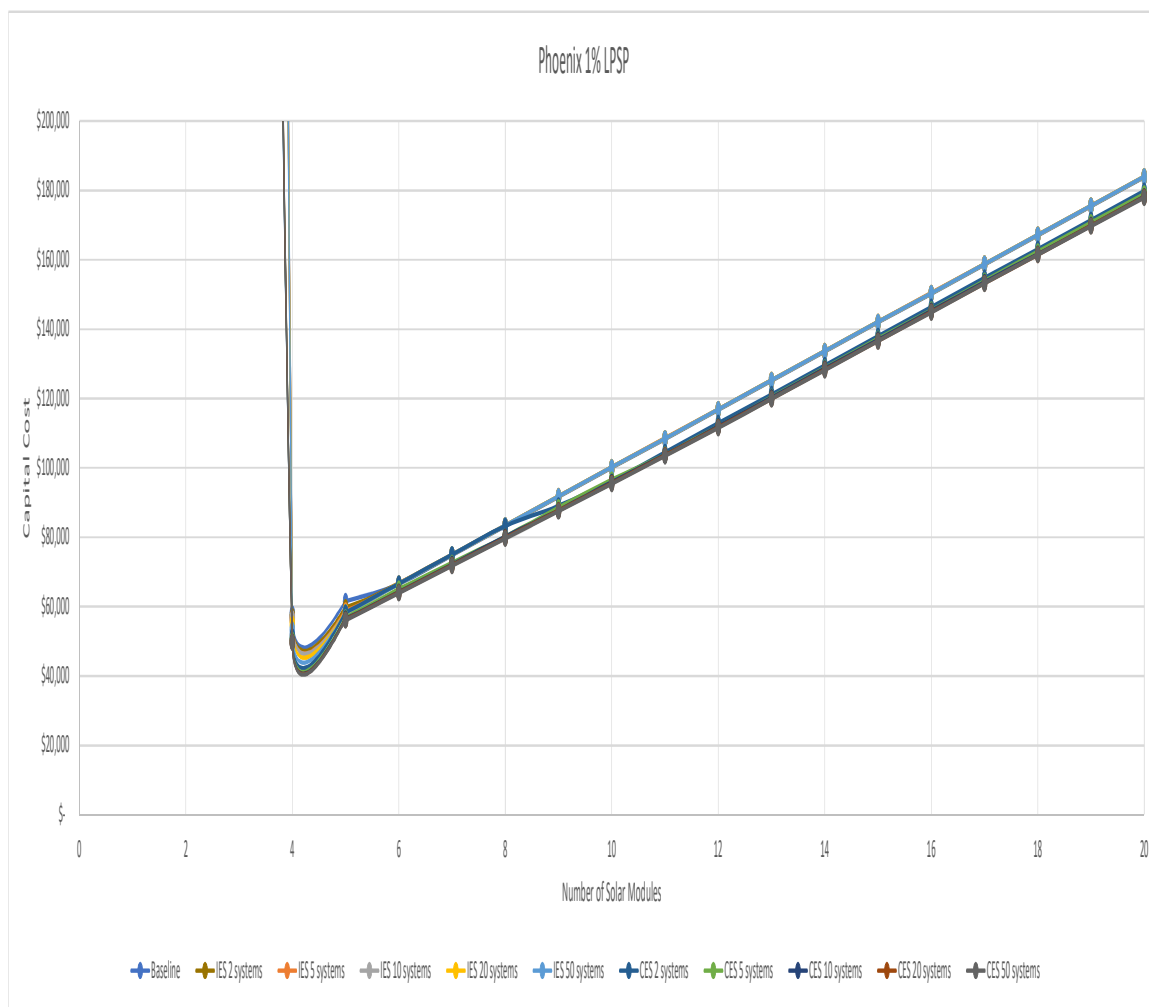


Figure 4.44. Results for varying number of systems given 1% LPSP required, June, 10% initial charge, and Phoenix

4.4.7 Little Rock

This section contains all case studies for the location of Little Rock (Figures 4.45 - 4.53) with a corresponding summary table (Table 4.4). Little Rock has a climate zone of 'Mixed-Humid' and a global normal irradiance of 4.0 - 4.5 kWh/sq.m/day. Little Rock fell in the middle among the geographic locations studied in terms of total cost per system.

Table 4.4. Summary Table for Little Rock showing the optimum configurations for each case from the Main Simulation.

Summary Table for Little Rock					
Operating Strategy	LPSP (%)	# of Systems	Optimum # of Solar Panels	# of Batteries (Average)	Capital Cost (Average)
Baseline	0.1	-	10	4.9	\$ 123,379
Baseline	0.2	-	9	5.4	\$ 119,457
Baseline	0.5	-	9	4.3	\$ 110,061
Baseline	1	-	9	3.6	\$ 104,634
IES	0.1	2	10	4.8	\$ 122,972
IES	0.1	5	10	4.8	\$ 122,477
IES	0.1	10	10	4.9	\$ 123,814
IES	0.1	20	9	5.6	\$ 120,917
IES	0.1	50	10	4.6	\$ 121,627
IES	0.2	2	10	4.3	\$ 118,760
IES	0.2	5	10	4.3	\$ 118,444
IES	0.2	10	9	5.3	\$ 118,701
IES	0.2	20	9	5.4	\$ 119,617
IES	0.2	50	9	5.3	\$ 118,333
IES	0.5	2	9	4.4	\$ 110,828
IES	0.5	5	9	4.4	\$ 111,282
IES	0.5	10	9	4.3	\$ 110,626
IES	0.5	20	9	4.3	\$ 110,715
IES	0.5	50	9	4.2	\$ 109,529
IES	1	2	9	3.6	\$ 104,753
IES	1	5	9	3.6	\$ 104,656
IES	1	10	9	3.5	\$ 103,870
IES	1	20	9	3.5	\$ 103,951
IES	1	50	9	3.4	\$ 103,057
CES	0.1	2	9	4.9	\$ 115,567
CES	0.1	5	9	4.7	\$ 113,533
CES	0.1	10	9	4.8	\$ 114,562
CES	0.1	20	9	4.5	\$ 111,828
CES	0.1	50	9	4.5	\$ 112,446
CES	0.2	2	9	4.3	\$ 110,585
CES	0.2	5	9	4.1	\$ 109,095
CES	0.2	10	9	4.2	\$ 109,492
CES	0.2	20	9	4.2	\$ 109,629
CES	0.2	50	9	4.1	\$ 108,947
CES	0.5	2	9	3.5	\$ 103,741
CES	0.5	5	9	3.4	\$ 103,327
CES	0.5	10	9	3.3	\$ 102,372
CES	0.5	20	9	3.3	\$ 102,724
CES	0.5	50	9	3.2	\$ 101,566
CES	1	2	8	3.7	\$ 96,781
CES	1	5	8	3.6	\$ 96,295
CES	1	10	9	2.6	\$ 96,532
CES	1	20	8	3.5	\$ 95,424
CES	1	50	8	3.4	\$ 94,578

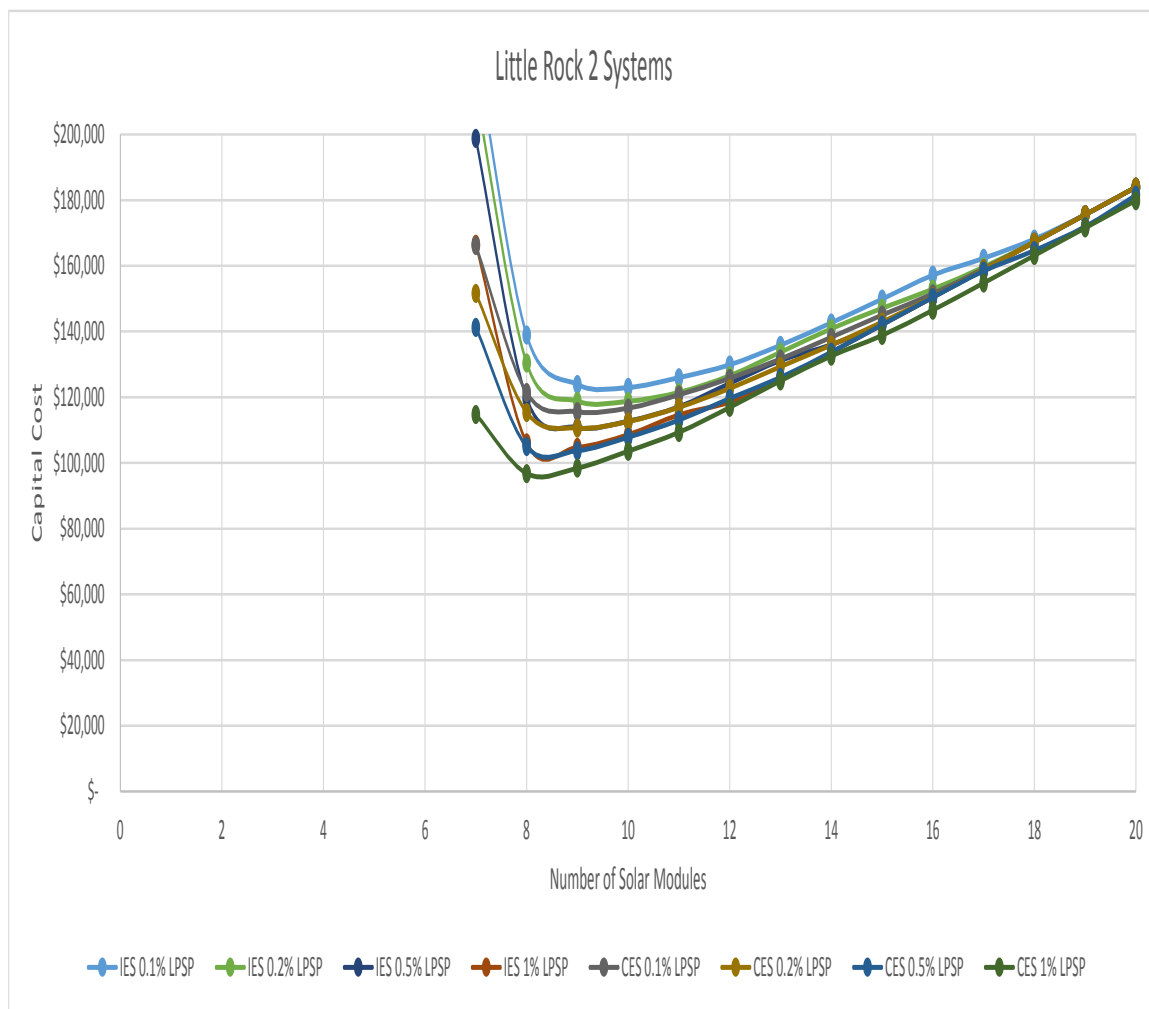


Figure 4.45. Results for varying LPSP required given June, 10% initial charge, 2 systems, and Little Rock

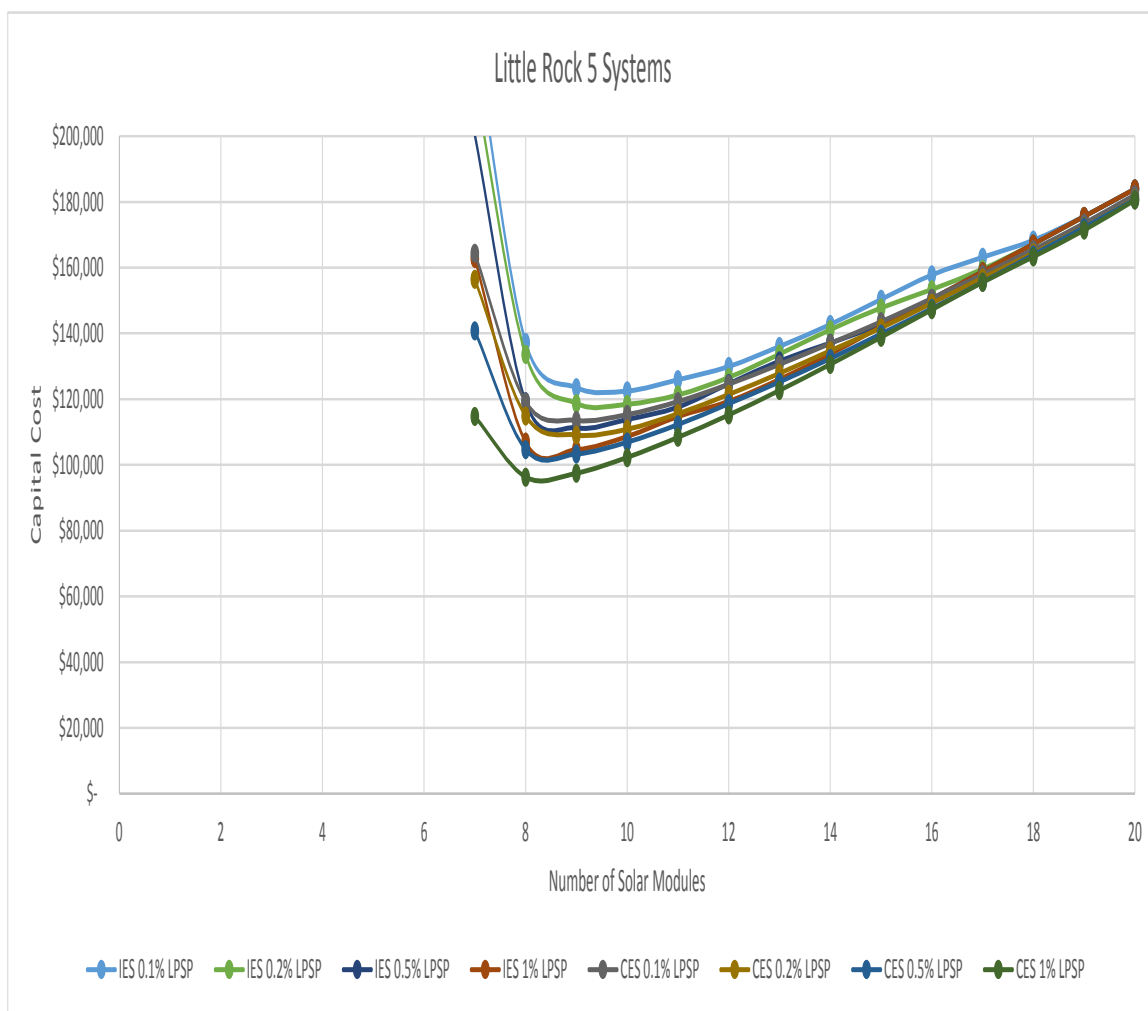


Figure 4.46. Results for varying LPSP required given June, 10% initial charge, 5 systems, and Little Rock

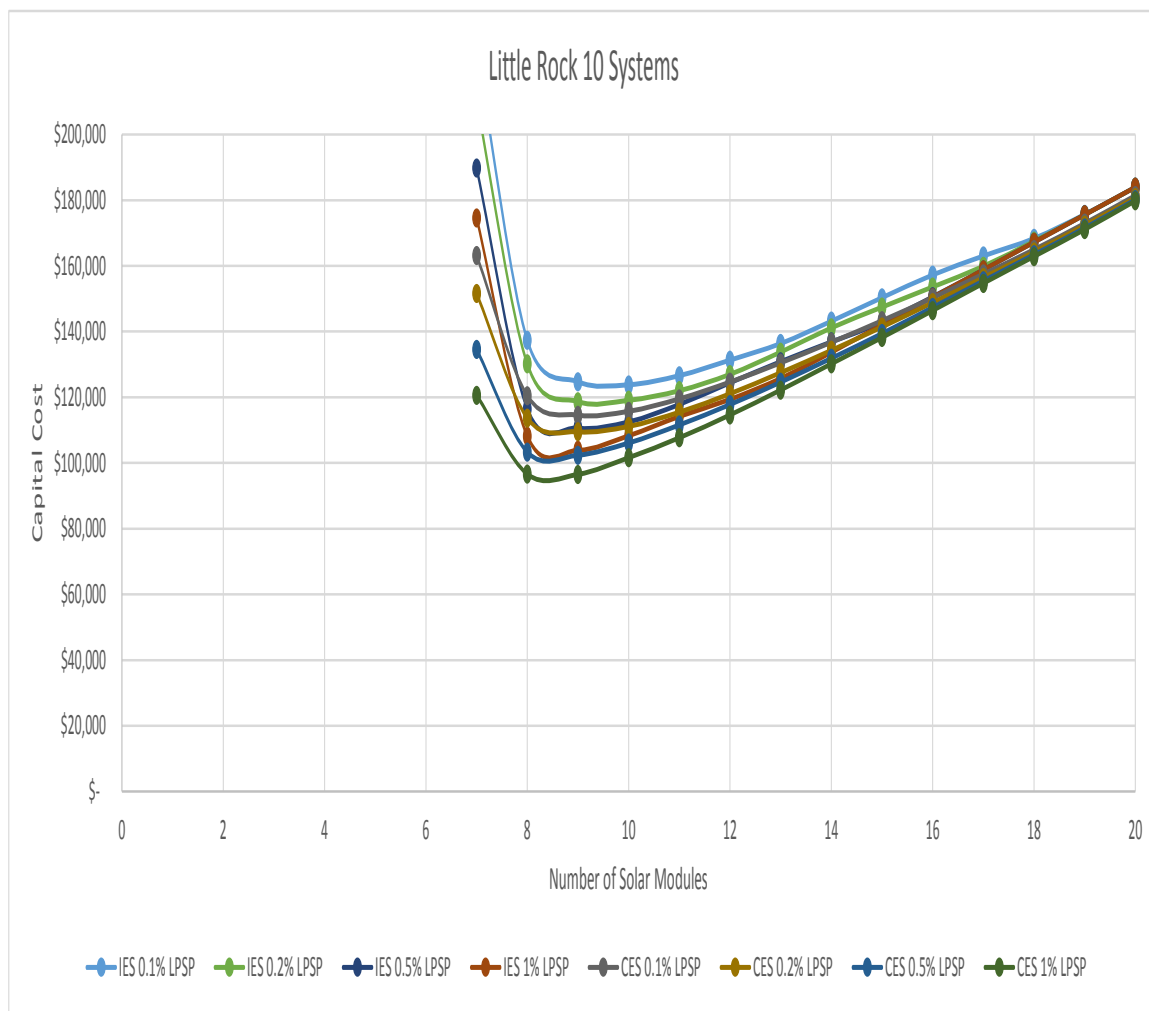


Figure 4.47. Results for varying LPSP required given June, 10% initial charge, 10 systems, and Little Rock

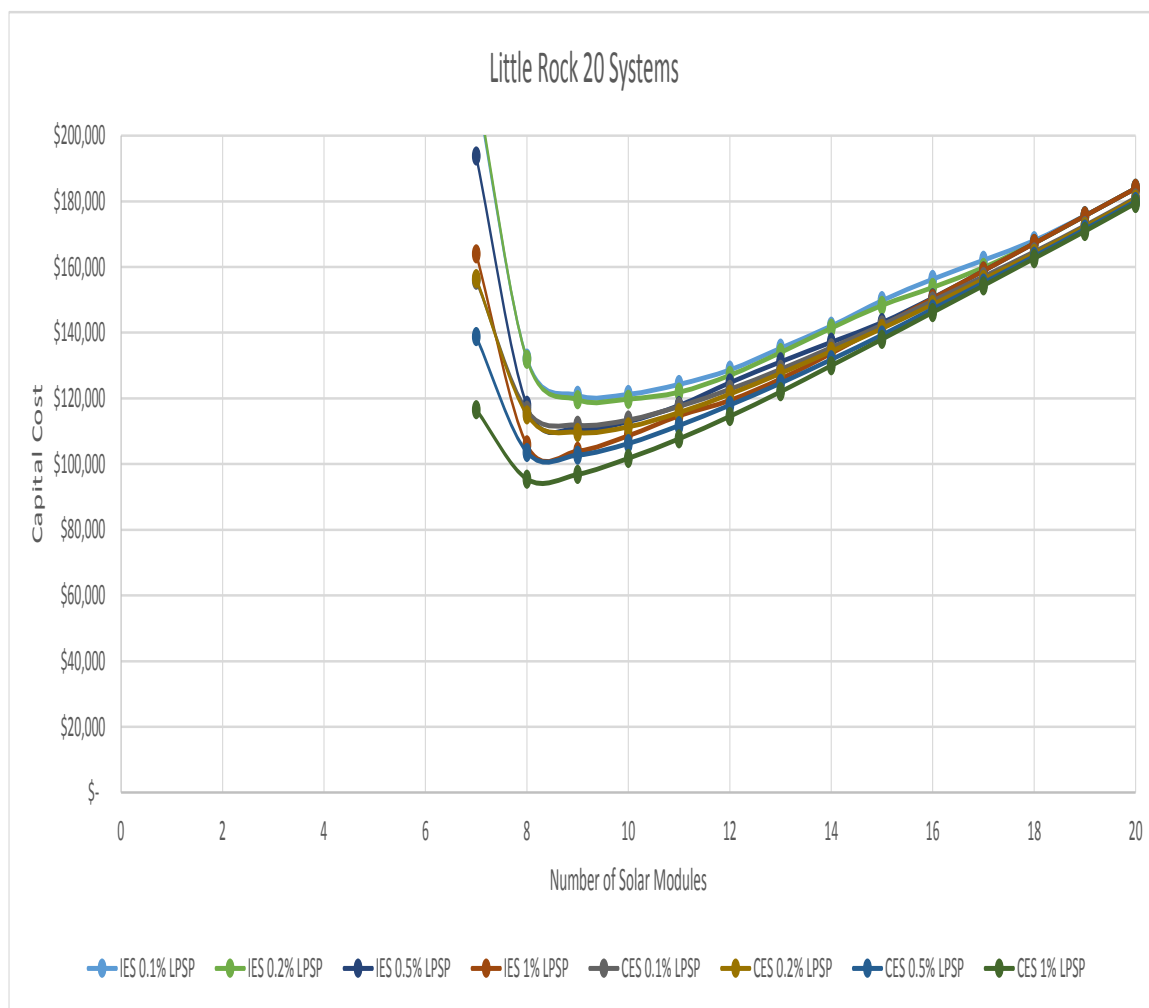


Figure 4.48. Results for varying LPSP required given June, 10% initial charge, 20 systems, and Little Rock

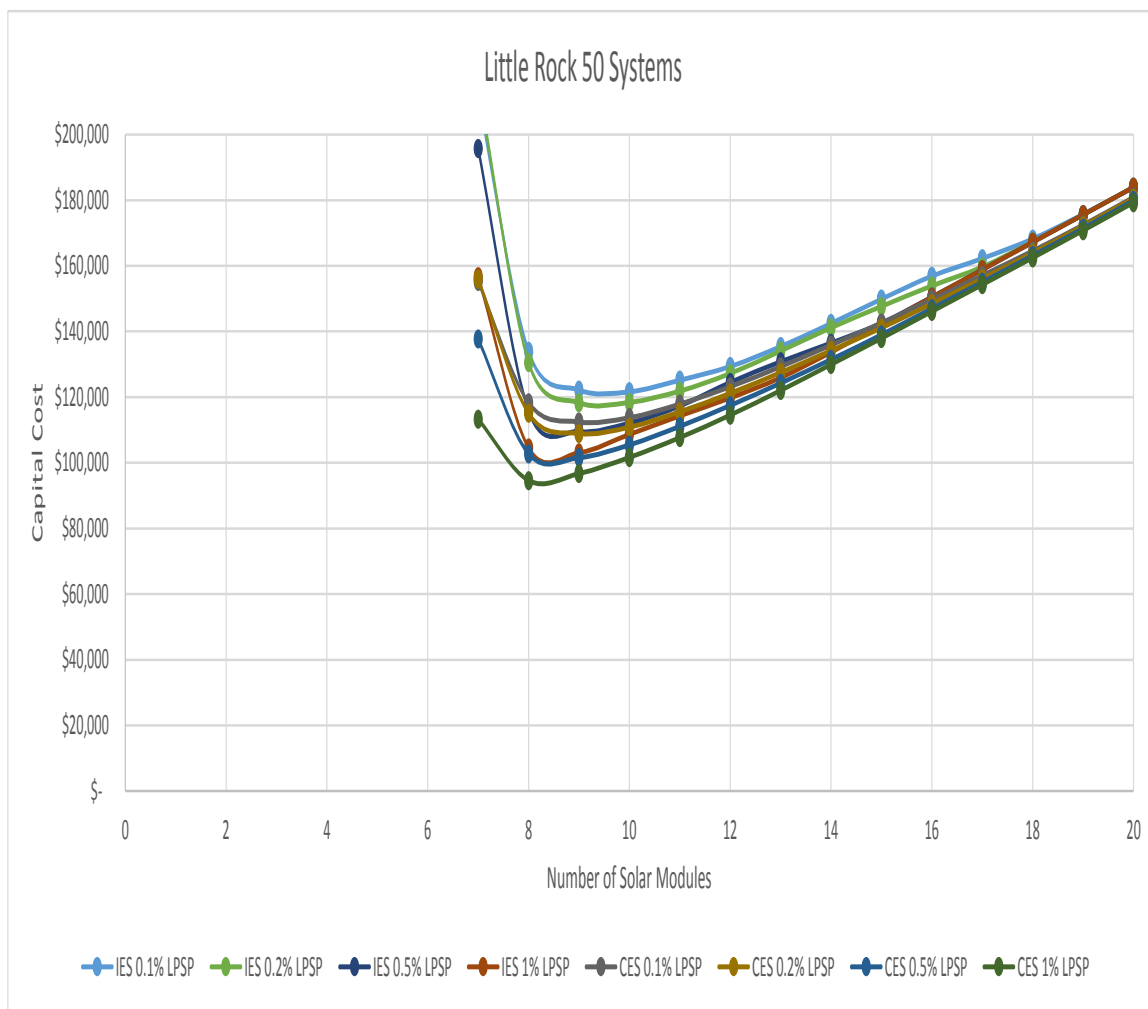


Figure 4.49. Results for varying LPSP required given June, 10% initial charge, 50 systems, and Little Rock

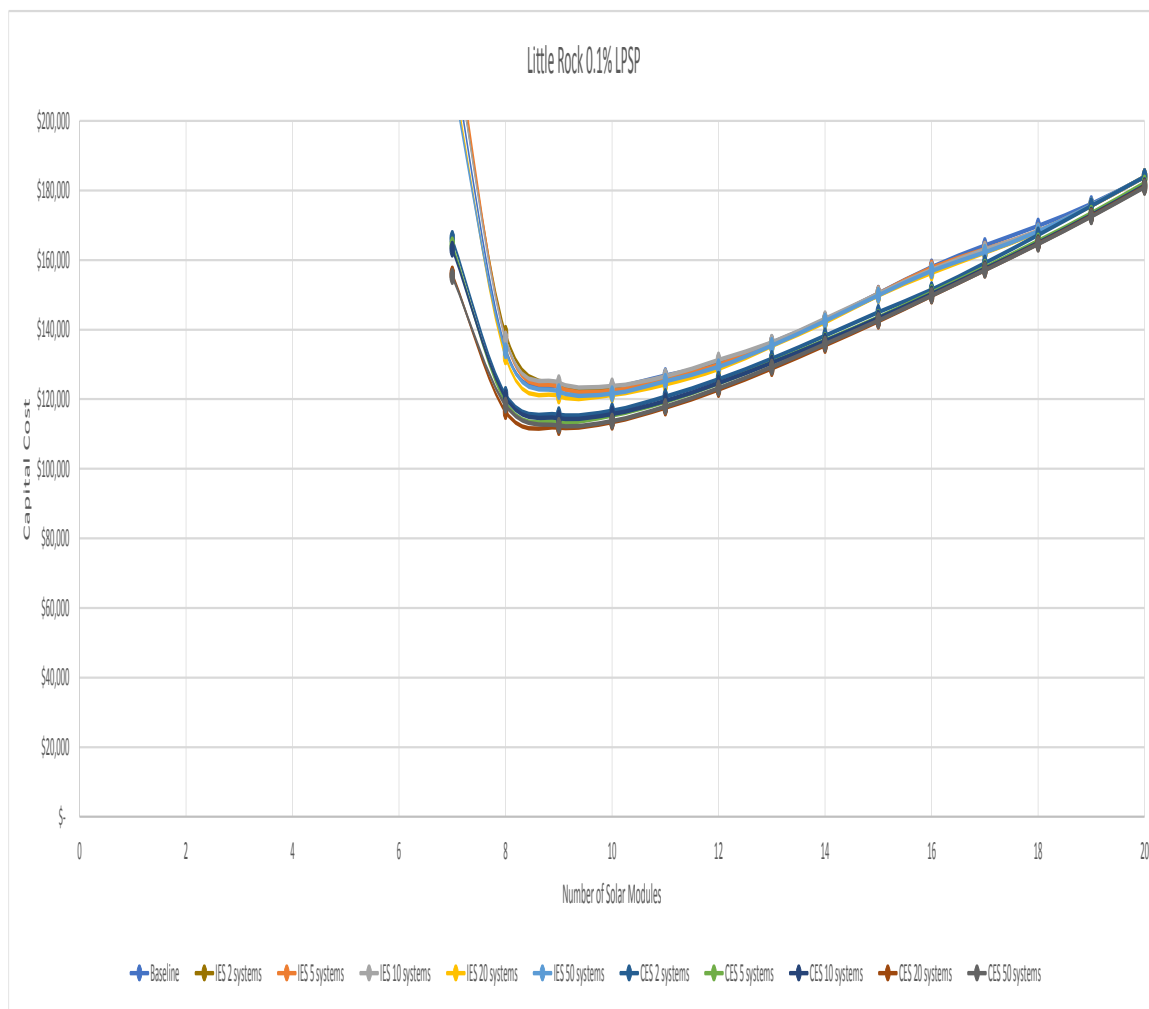


Figure 4.50. Results for varying number of systems given 0.1% LPSP required, June, 10% initial charge, and Little Rock

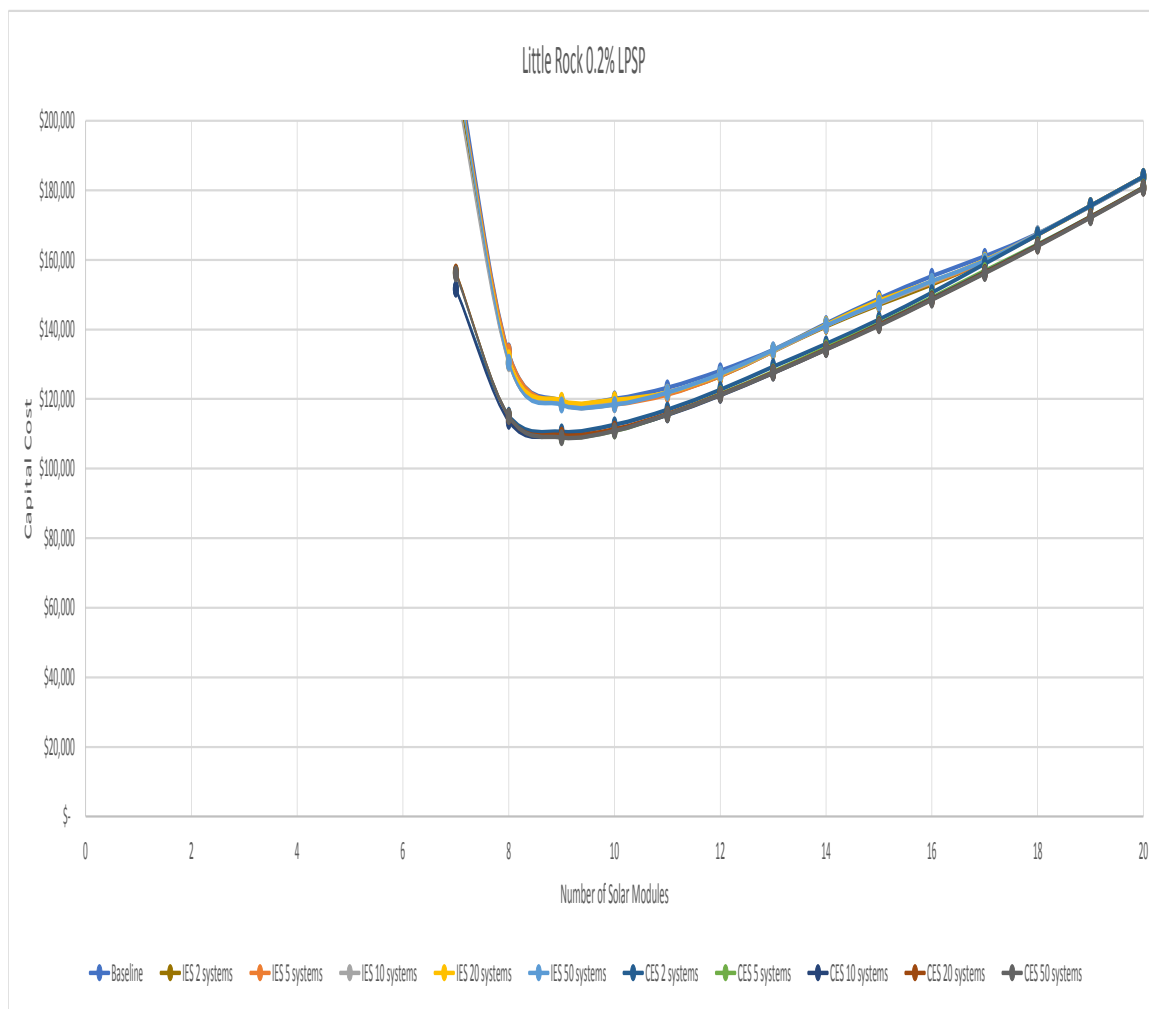


Figure 4.51. Results for varying number of systems given 0.2% LPSP required, June, 10% initial charge, and Little Rock

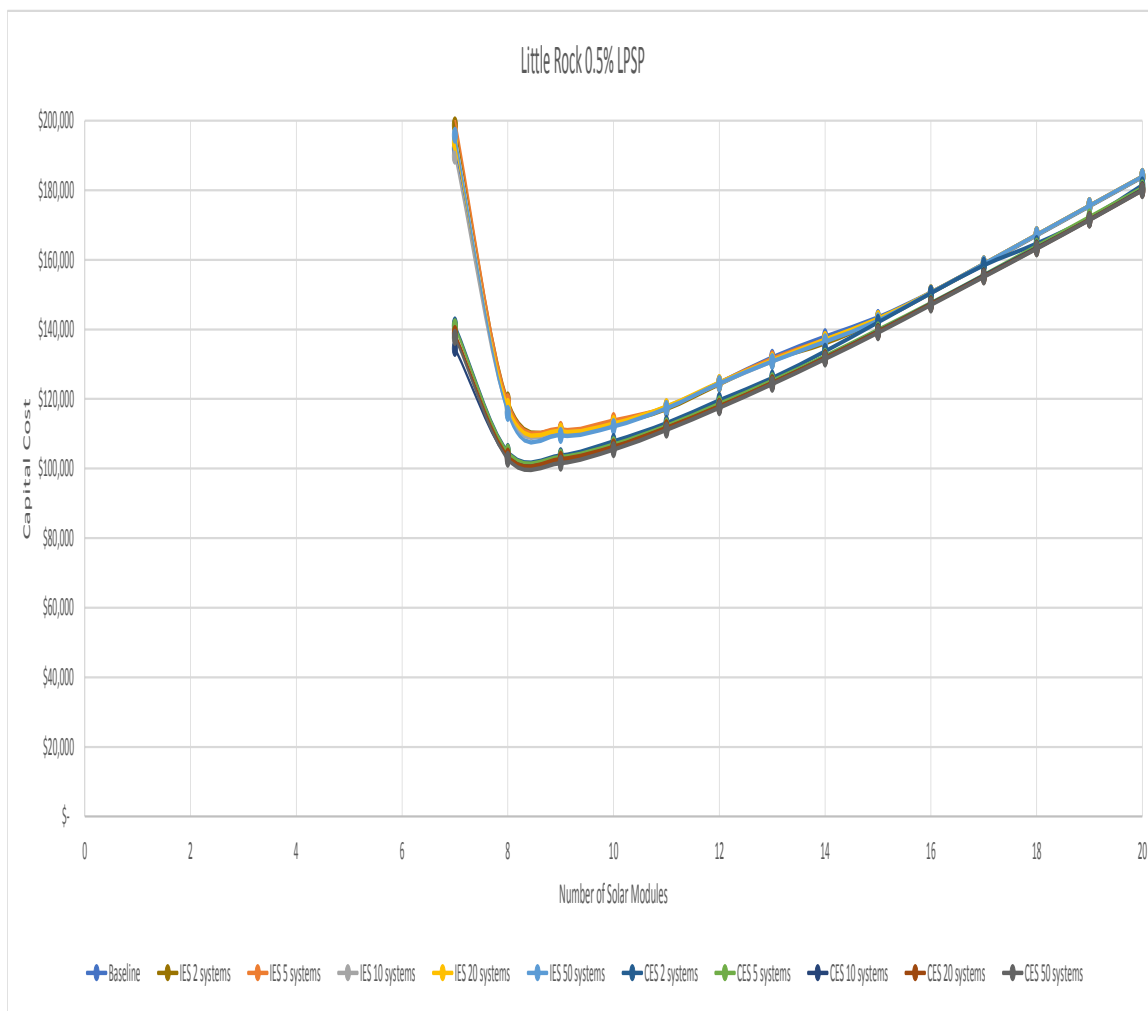


Figure 4.52. Results for varying number of systems given 0.5% LPSP required, June, 10% initial charge, and Little Rock

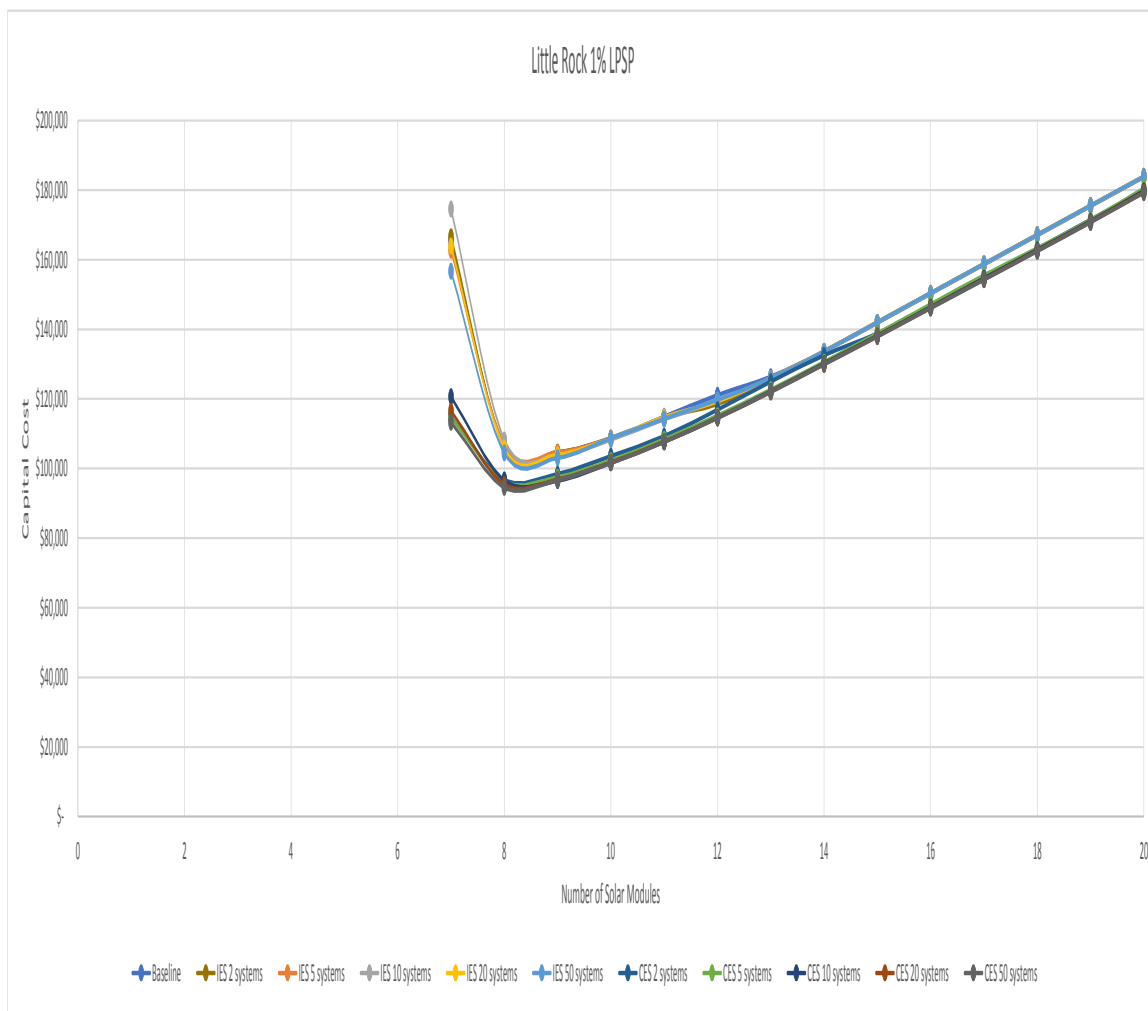


Figure 4.53. Results for varying number of systems given 1% LPSP required, June, 10% initial charge, and Little Rock

4.5 Summary

The results from this thesis are summarized in Table 4.5. This table explains the cases investigated, their effect on total cost, the associated figures for each case, comments, and future work.

Table 4.5. Summary table showing each studied effect, the cases considered, where to find the associated figures, comments, and future work.

Studied Effect	Cases	Effect on Total Cost	Figures	Comments	Future Work
Initial Charge	(Indianapolis) 1%, 5%, 10%, 15%, 20%, 100%	No effect for March and July. For November the lower initial charge cases of 1% and 5% have higher cost, presumably due to difficulties overcoming low initial charge condition in winter months.	July (4.1 - 4.3) March (4.4 - 4.6) November (4.7 - 4.9)	The 100% and 1% cases are not typical. Typical values are between 5% and 20%. 10% is used throughout the rest of the simulations.	More research is needed to show how initial charge might affect the rest of the months in the year.
Load Variation	1. Variation in load simulated by load shifting explained in section 3.4.1 2. No Variation in load	Inconsistent. For San Antonio case, having load variability improved system economics. For Indianapolis, having load variability did not improve system economics	San Antonio (4.16) Indianapolis (4.17)	This studies solution for simulating load variability (horizontal shift) was not adequate to fully study the effect of load variation.	Consider more advanced load simulation techniques
Starting Month	All months (January - December)	The months of January, February, March, July, and December give non-typical results compared to others, which compare very reasonably.	Indianapolis (4.10 - 4.12) San Antonio (4.13 - 4.15)	The month of June is chosen for the rest of the simulation. Winter months showed higher cost. If you must go off-grid during a winter month, use an external power source to increase initial charge.	HOMER does not include a method for analyzing the starting month of simulation. Starting month should be included especially if going off-grid beginning in a winter month.
# of SAPV Systems	2, 5, 10, 20, 50	No significant effect. The difference in two systems and fifty for IES and CES cases was no more than \$2,000 per system.	Indianapolis (4.23 - 4.26) Erie (4.32 - 4.35) Phoenix (4.41 - 4.44) Little Rock (4.50 - 4.53)	The hypothesis was that increasing the number of systems would decrease the cost per system. Because two systems showed the same cost as fifty systems, it may only be necessary to find one other person to trade with to receive a savings with the CES strategy.	This result needs to be tested with more advanced load simulation techniques
Required Reliability	0.1%, 0.2%, 0.5%, 1% LPSP (9, 18, 45, 90 hours of outage allowed)	Consistent and predictable. As the required reliability increased (number of hours of outage allowed went down) the cost went up.	Indianapolis (4.18 - 4.22) Erie (4.27 - 4.31) Phoenix (4.36 - 4.40) Rock (4.45 - 4.49)	Because the cost of going off-grid is so high, it is likely that sacrificing reliability and changing energy consumption habits is necessary to make it affordable.	Even lower levels of required reliability should be considered to determine how much reliability must be sacrificed to compete with utility electricity prices.
Geographic Location	Indianapolis, Indiana; Phoenix, Arizona; Little Rock, Arkansas; Erie, Pennsylvania	Phoenix was considerably cheaper than any of the other locations. Erie had the highest cost for going off-grid. This result was expected because of each geographic location's load and solar radiation profiles.	Indianapolis (4.18 - 4.26) Erie (4.27 - 4.35) Phoenix (4.36 - 4.44) Rock (4.45 - 4.53)	Summary tables for each location are given in Tables 4.1 - 4.4. San Antonio was not included in this analysis due to non-realistic (>\$160,000 per system) results.	More locations should be analyzed for a full analysis of the climate zones and solar irradiation profiles existent across the US.
Interconnection Type	1. Baseline (No Interconnection) 2. Interconnected Energy Sharing (IES) 3. Centralized Energy Sharing (CES)	CES provided a 7% - 10% lower cost than other operating strategies even with only two systems. The IES case showed a very small, but consistent, improvement over the baseline case given that an interconnection cost was included.	Throughout Chapter: 4	The interconnection cost for IES and CES cases were taken as a rough estimate and any loss to efficiency by interconnecting was not considered.	Interconnection cost and losses to efficiency should be more carefully determined.

5. CONCLUSIONS

5.1 Conclusions

In conclusion, the purpose of this thesis research was to investigate sizing methodologies for stand-alone PV systems (SAPV) and off-grid transactive microgrids to compare conventional (isolated consumption), centralized energy sharing (CES), and interconnected energy sharing (IES) operating strategies.

The idea for improvement of the conventional strategy is that if a transactive microgrid can be established between SAPV systems they could sell power when their batteries are full and buy power when their batteries are empty, increasing their reliability and improving their utilization of solar energy, theoretically reducing total cost depending on the cost to implement the energy infrastructure. The transactive microgrid has just recently been enabled with the advent of 'Blockchain', a decentralized ledger which can allow for the open exchange of power between homes. Now, communities can band together to centrally store their PV and ESS (CES) or distribute PV and ESS and establish a trading system (IES). Before this research, there were no analytical studies on the pricing of transactive microgrids which used conventional SAPV sizing strategies or that considered off-grid operation.

The goal of this thesis was to develop a tool for comparing operating strategies of SAPV systems (conventional, CES, and IES). This goal was accomplished through development of a MATLAB program which directly compares the three operating strategies. Although existing software such as HOMER do not include transactive microgrid modeling this research shows that it could be easily done especially for the CES case.

The problem statement for this thesis was as follows: "What type of SAPV energy sharing strategy provides the lowest total cost? For each energy sharing strategy, how

does initial battery charge, load variation, starting month, number of SAPV systems, geographic location, and required reliability affect total cost?”

The results of this thesis were summarized in Table 4.5. The CES strategy improved initial cost by 7% to 10% compared to the baseline and IES cases. The IES case saved less than 1% compared to the baseline but did show a consistent savings considering that an interconnection cost was included. Initial charge was found to have an effect in November but not in March or July. This indicates that initial charge might be more of an issue in a winter month but more research should be conducted to show the effect for every month of the year. Load variability did not show consistent results, presumably due to the load simulation method, which can be improved by adding peak shifting instead of just time shifting. The number of systems involved in a transactive microgrid did not seem to affect the initial cost for the CES or IES case. This may be due to the load simulation method but it may also indicate that only one other system is necessary to receive the benefits from an energy sharing operating strategy. Geographic locations studied showed a large effect on total cost with Phoenix being considerably cheaper than other locations studied, Erie having the highest cost, and Little Rock and Indianapolis following closely behind Erie. This result was expected due to the associated load and solar radiation profiles of each geographic location. When the reliability requirement was relaxed, allowing for more hours of outage per system in a year, the cost went down predictably.

Going off-grid with solar and battery is expensive and difficult. It is likely that in order to go off-grid with favorable economics using any of the proposed operating strategies it is necessary to reduce the reliability requirement, adopt energy saving consumption habits, and choose a favorable geographic location.

5.2 Future Work

The results of this thesis could be expanded by:

- Improving load simulation by adding peak shifting

- Considering new variables in the load profile (high vs. low, commercial, industrial, vacations, economic status, number of occupants, home-size, number of working adults, night-owl vs. early bird, etc.)
- Researching typical residential load variability, no study was found which determines the typical variation between residential loads
- Upgrading model equations to include solar angles, clearness index, dynamic battery model, and charge controller behavior
- Revising optimization method and search space so that smaller solar and energy storage sizes are considered
- Adding day-level correlations to the Markov solar simulation model. Current model assumes that solar irradiation is 'memoryless' which is generally true on an hourly basis but not on a daily basis. Current model accurately forecasts how many sunny and shady days there will be in a month but not the order in which they occur.
- Conducting a real world case study
- Investigating isolated locations such as polar and tropical where the idea might make more sense
- Developing new energy sharing strategies (all sharing equally, determine the most equitable sharing method, trying to spread the sharing out among houses)
- Including storage from electric vehicles, smart load control between systems (delaying unimportant loads, speeding up divertable loads), and conservative energy consuming habits
- Considering wind energy generation for transactive microgrids. Wind complements solar nicely by producing more consistent power during the winter but a high capital cost usually hinders residential applications

- Studying the physical interconnection between systems (determine efficiency losses, develop a generic cost estimate for interconnection, show possible configurations, investigate existing equipment such as charge controllers and inverters to determine how these systems may work)
- Developing a graphic user interface to make the tool more user friendly

These initial results need to be expanded to draw substantiated conclusions, but a MATLAB tool is now available to advance this research. This tool could be easily incorporated into existing software such as HOMER. The CES case in particular shows promising potential for improving the baseline and furthering research in this field.

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APPENDIX

A. APPENDIX

A.1 Matlab Code

```

%Main.m
clc

=====
% This main project file simulates the sizing of multiple SAPV
% systems for 3 possible cases: Isolated Self Consumption (Baseline),
% Centralized Energy Sharing, and Interconnected Energy Sharing.
=====

%Excel File Name
SAPV_Analysis = 'San_Antonio_20Systems_10Trials_45hours.xlsx';
%SAPV_Analysis = 'San_Antonio_Baseline_5Trials_45hours.xlsx';
%SAPV_Analysis = 'DELETE.xlsx';

%Number of SAPV systems to optimize.
Number_of_SAPV_Systems = 2;

%Number of trials to perform. Computation time should be considered.
Number_of_Trials = 1;

%Number of acceptable outage hours.
LPSP_Count = 45;
%9 hours ensures ~0.1% LPSP reliability
%18 hours ensures ~0.2% LPSP reliability
%27 hours ensures ~0.3% LPSP reliability
%36 hours ensures ~0.4% LPSP reliability
%45 hours ensures ~0.5% LPSP reliability
%90 hours ensures ~1% LPSP reliability

%Whole number of years you wish to simulate results. (typically 1)
Simulation_years = 1;
if Simulation_years ~= 1
    fprintf('Warning: Simulation years are not equal to 1!\n\n')
end

%TMY3_Input stores Solar and Load data for use in simulation from TMY3
[Solar_Data, Load_Data] = TMY3_Input(Number_of_SAPV_Systems, Number_of_Trials);

```

Figure A.1. Main Project File (1/3)

```

%=====
%Component Specifications for Solar Panels, Battery, Charge Controller,
%Inverter, and Wiring. Range of PV configurations is input, initial guess
%for required battery capacity is input. Each SAPV system is considered to
%have the same component specifications.
Component_Specifications;

%=====
%Solar Irradiation and PV output are simulated based on historical data.

%Generates a cumulative STM based on the provided solar data. Maximum_Solar
%gives the largest value of solar irradiation in the dataset
[Maximum_Solar,Big_Cumulative_STM] = Solar_Cumulative_STM_Generator(Solar_Data);

%Takes the cumulative STM from 'Solar_Irradiation_Cum_STM_Generator' and
%generates simulation results.
Solar = Solar_Irradiation_Simulator(Number_of_Trials,Simulation_years,Maximum_Solar,Big_Cumulative_STM);

%PV output energy for each possible PV configuration is calculated (every
%hour) based on solar irradiation simulated. Total_PV_Generation is the
%total PV output from each system over the whole simulation. (Used to
%calculate %PV_Generation Utilization.)
[PV_Output,Total_PV_Generation] =
PV_Output_Calculator(Solar,Number_of_Trials,Solar_Panel_Range,Solar_Panel_Rating,PV_Derating_Factor);

%=====
%Load demand is simulated once for each SAPV system based on typical
%residential load profile and then for the central battery case.
[Hourly_Load,Shared_Hourly_Load] = Load_Demand_Simulator(Number_of_Trials,Simulation_years,Load_Data);

%=====
% Baseline: Energy storage analysis is performed based on the PV output
% energy and load demand required. Battery State of Charge (SOC) is
% calculated (every hour), if battery SOC exceeds 100% that energy is
% stored in energy excess array and LOPVG count is incremented, if battery
% SOC breaks 0% the amount of energy not supplied is stored in energy
% deficit array and LOS count is incremented.
Baseline_Table=Baseline_ESS_Analysis(Hourly_Load,PV_Output,Total_PV_Generation,Battery_Capacity,
Battery_Efficiency,Initial_Battery,Solar_Panel_Range,Battery_Cost,Solar_Panel_Cost,SAPV_Analysis,LPSP_Count
);

```

Figure A.2. Main Project File (2/3)

```

%=====
% Centrally stored battery and shared solar panels. Acts as one SAPV system with
% combined loads and PV output. Calculates difference in storage and load,
% battery required and capital cost.
Central_Table=Central_ESS_Analysis(Number_of_SAPV_Systems,Shared_Hourly_Load,PV_Output,Total_PV_Generation,
Battery_Capacity,Battery_Efficiency,Initial_Battery,Solar_Panel_Range,Battery_Cost,Solar_Panel_Cost,
SAPV_Analysis,LPSP_Count);

%=====
% Interconnected Energy Sharing (each SAPV system has its own battery and
% solar panel configuration but systems are able to share energy: If
% battery SOC is equal to 100%, that SAPV system will sell its energy for
% that hour to another SAPV system (if another SAPV system can take that
% energy without going over 100% SOC itself).

% If battery SOC is equal to 0%, that SAPV system will buy its energy for
% that hour from another SAPV system (if another SAPV system can sell
% energy without reaching 0% SOC itself)
Table_IES=IES_Analysis_N_Systems(Hourly_Load,PV_Output,Total_PV_Generation,Battery_Capacity,
Battery_Efficiency,Initial_Battery,Solar_Panel_Range,Battery_Cost,Solar_Panel_Cost,SAPV_Analysis,
LPSP_Count);

%=====
% In each case: technical parameter will be calculated (from energy deficit
% array), if technical parameter is not met then battery capacity is
% incremented, if technical parameter is met that configuration will be
% stored for further testing, optimum configurations will be sorted based
% on economical parameter selected, and finally the best configurations can
% be compared based on additional parameters such as (%PV Generation
% Utilization (energy excess array), and Levelized Cost of Energy (compare
% to utility prices).

```

Figure A.3. Main Project File (3/3)

```

function [Solar_Data, Load_Data] = TMY3_Input(Number_of_SAPV_Systems,Number_of_Trials)
%TMY3_INPUT The purpose of this 'function' is to input TMY3 Solar and Load Data.

Load_Data = zeros(8760,Number_of_SAPV_Systems,Number_of_Trials);

%Load TMY3 Solar data for geographical location
load Erie_PA.txt
load Indianapolis_IN.txt
load LittleRock_AR.txt
load Phoenix_AZ.txt
load Reno_NV.txt
load SanAntonio_TX.txt

%Determines which TMY3 location is actually used. Make sure load matches!
Solar_Data = circshift(SanAntonio_TX,-4344); %circshift(A,-3624) starts the simulation on July 1st instead
of January 1st

%Load TMY3 residential load data for geographical location
load Erie_PA_LOAD.txt
load Indianapolis_IN_LOAD.txt
load LittleRock_AR_LOAD.txt
load Phoenix_AZ_LOAD.txt
load Reno_NV_LOAD.txt
load SanAntonio_TX_LOAD.txt

%Make sure that Load Data matches geographically with Solar Data!!! The
%first system is constant for each trial.
Load_Data_1 = circshift(SanAntonio_TX_LOAD,-4344);

for trial = 1:Number_of_Trials
for system = 1:(Number_of_SAPV_Systems)
    random_hour = randi(7); %Generates random number between (a,b) where random = a+(b-a)*rand()
    Load_Data(:,system,trial) = circshift(Load_Data_1,random_hour-4); %Y = circshift(A,K) circularly
    shifts the elements in array A by K positions. circshift(A,3) 'lags by three hours'
    random_day = randi(7);
    Load_Data(:,system,trial) = circshift(Load_Data_1,24*(random_day-4));
end
end
end

```

Figure A.4. TMY3_Input.m


```

%Component_Specifications.m

% The purpose of this script is to input component specifications.
    %%%%%%%%% Solar Panels %%%%%%%%%
%Solar Panel Rating
Solar_Panel_Rating = 3000; % in Watt.
% Solar_Panel_Rating = input('Please enter the solar panel rating.');
```

%Solar Panel Cost

```

Solar_Panel_Unit_Cost = 4877; % Price for one Solar Panel in U.S. Dollars / Watt. If
given as average installed cost/W then no need to calculate labor cost or inverter cost
%Solar_Panel_Cost = input('Please enter the price for one solar panel.');
```

%Solar Panel Installation Cost

```

Solar_Panel_Installation_Cost = 1500; %Price of installation for one solar panel. Not
necessary if solar panel cost given as the average installation cost /W.
```

%Total Cost per Solar Panel

```

Solar_Panel_Cost = Solar_Panel_Unit_Cost + Solar_Panel_Installation_Cost;
```

%Range of Solar Panels to Test. %Give as a range of solar panel numbers to
%optimize or one number. i.e Solar_Panel_Range = [1 6 9 16]
%Number_of_Configurations variable would be 4.
Solar_Panel_Range = (5:1:50);

%PV Derating factor is a scaling factor that HOMER applies to the PV array
%power output to account for reduced output in real-world operating
%conditions compared to the conditions under which the PV panel was rated.
% Use the derating factor to account for such factors as soiling of the
% panels, wiring losses, shading, snow cover, aging, and so on. If you
% choose not to explicitly model the effect of temperature on the PV array,
% include temperature-related effects in the derating factor.
PV_Derating_Factor = 0.731;
 %%%%%%%%% Battery %%%%%%%%%

%Battery Capacity

```

Battery_Capacity = 13.5; % Capacity of Battery in kWh
% Battery_Capacity = input('Please enter the battery capacity');
```

%Battery Efficiency

```

Battery_Efficiency = 0.90; % Round-trip efficiency of battery storage. Using for charging
%Battery_Efficiency = input('Please enter the battery efficiency');
```

%Battery Cost

```

Battery_Unit_Cost = 5900; % Price for one battery. If given as the average installation
cost/W then no need to calculate labor cost or controller cost
%Battery_Cost = input('Please enter the battery cost');
```

%Battery Hardware Cost

```

Battery_Hardware_Cost = 700; %Price of hardware for each battery. Not necessary if using
average installation cost/W for Battery Cost
```

%Battery Installation Cost

```

Battery_Installation_Cost = 1500; %Price of installation for each battery. Not necessary
if using average installation cost/W for Battery Cost
```

%Total Cost per Battery

```

Battery_Cost = Battery_Unit_Cost + Battery_Hardware_Cost + Battery_Installation_Cost;
```

%Initial Guess for Number of Batteries. Used for every case

```

Initial_Battery = 1;
%Initial_Battery = input('Please enter the initial guess for number of batteries');
```

Figure A.5. Component_Specifications

```

function [Total_Maximum,BIG_STM_CUM] = Solar_Cumulative_STM_Generator(Solar_Data)
%The purpose of this function is to generate a cumulative STM based on the provided solar data.

%Reshapes the months into a 12xNumber_of_years matrix, so all months can be worked on consecutively for developing the
%set of STMs. (Not necessary for TMY3 data)
Months = [31 31 30 31 30 31 31 28 31 30 31 30]; %Solar data begins in July!!
size_of_months = size(Months);
month_reshape = size_of_months(1);
%rmnth = reshape(Months,(month_reshape/Number_of_years),(Number_of_years));

%=====
%***** Loads Solar Data *****
%=====

%Initializes variable datapoints
datapoints = 0;

%Initialize the BIG matrix of hourly values of solar data for all months. Be aware, months not having 31 days will need
%to be handled (Not necessary for TMY3)
BIG = zeros(month_reshape,31,24);

%Populate the BIG matrix with the solardata from the text file
for i1 = 1:12 %*Number_of_years
    for d1 = 1:Months(i1)
        for h1 = 1:24
            datapoints = datapoints + 1;
            BIG(i1,d1,h1) = round(Solar_Data(datapoints),-1);
            %But we need data from the same month eventually combined!
        end
    end
end

%Gives maximum solar radiation possible rounded to the nearest 10.
Total_Maximum = round(max(Solar_Data)*0.1)*10;

%=====
%Build STM for all months. 24 hours a day x 12 months = 288 STM matrices.
%The result of this code is a tally of the number of times of going from
%one solar radiation value to another solar radiation value, for each hour
%of each month.
%=====
BIG_STM = zeros(12,24,((Total_Maximum/10)+1),((Total_Maximum/10)+1));

for m_STM = 1:12 %Each month of data, %for y_STM = 1:Number_of_years %Each year of data

```

Figure A.6. Solar_Cumulative_STM_Generator.m (1/2)

```

for day_STM = 1:Months(m_STM) %Number of days in the month
    for hourpoint = 1:23 %Helps with calculation. Hour 24+1 doesn't make sense. Just assume that midnight is always
        dark.
            initial_value = (BIG(m_STM,day_STM,hourpoint)/10)+1;
            next_value = (BIG(m_STM,day_STM,hourpoint+1)/10)+1;
            BIG_STM(m_STM,hourpoint,initial_value,next_value) = BIG_STM(m_STM,hourpoint,next_value)+1;
        end
    end
end
%====
%Builds up the transition probabilities within the STM matrix. 23 hourly transitions are used because of the hour 24 +1
%in the last section. Assume midnight is always dark and doesn't require a transition probability.
%====
BIG_STM_PROB = zeros(12,23,((Total_Maximum/10) +1),((Total_Maximum/10)+1));
for m_STM_p = 1:12
    for h_STM_p = 1:23
        for i_p = 1:((Total_Maximum/10) + 1)
            BIG_STMrowsum = sum(BIG_STM(m_STM_p,h_STM_p,i_p,:));
            if BIG_STMrowsum == 0
                BIG_STMrowsum = 1;
            end
            for j = 1:((Total_Maximum/10)+1)
                BIG_STM_PROB(m_STM_p,h_STM_p,i_p,j) = BIG_STM(m_STM_p,h_STM_p,i_p,j)/BIG_STMrowsum;
            end
        end
    end
end
end
%====
%Converts BIG_STM_PROB to percentage
BIG_STM_PERCENT = BIG_STM_PROB*100;
%====
%Generates the cumulative probability function based on the transition probabilities determined above.
%====
BIG_STM_CUM = zeros(12,23,((Total_Maximum/10)+1),((Total_Maximum/10)+1));
for m_STM_cum = 1:12
    for h_STM_cum = 1:23
        for i_cum = 1:((Total_Maximum/10)+1)
            cum_STM_sum = 0;
            for j_cum = 1:((Total_Maximum/10)+1)
                BIG_STM_CUM(m_STM_cum,h_STM_cum,i_cum,j_cum) =
                    BIG_STM_CUM(m_STM_cum,h_STM_cum,i_cum,j_cum)+cum_STM_sum;
                cum_STM_sum = BIG_STM_CUM(m_STM_cum,h_STM_cum,i_cum,j_cum);
            end
        end
    end
end
end
end
end

```

Figure A.7. Solar_Cumulative_STM_Generator.m (2/2)

```

function [Solar] = Solar_Irradiation_Simulator(Number_of_trials,Simulation_Years,Total_Maximum,BIG_cum_STM)
%The purpose of this function is to take the cumulative STM from 'Solar_Irradiation_Cum_STM_Generator' and
%generate simulation results.

%Variable Months gives number of days in each month (No Leap Year)
Months = [31 31 30 31 30 31 31 28 31 30 31 30]; %Solar data begins in July!!

%Initialize Solar
Solar = zeros(8760*Simulation_Years,Number_of_trials);

for tr=1:Number_of_trials
%Generate a matrix of random number (hour, day, month), but choose to yield only 12 months of results. This
%is making note of the fact that there will likely be MORE than 12 months of data being used to make the
%STMs. So, define a new variable for the number of months you
%actually want to simulate.
m_sim = 12*Simulation_Years;
A = 100*rand(24,31,12*Simulation_Years);

%Determine the solar insolation level based on the cumulative probability function and assign (-1 values
%that will be removed later. They indicate values for days that don't exist, such as February 30th. All
%other day values that do exist will replace the '-1' values with
%real solar values.
Sol_Level = zeros(24,31,m_sim); % (hour,day,month)
Sol_Level = Sol_Level - 1;

%Provides a repeating set of 12 months
for m_calc = 1:m_sim
m_act = mod(m_calc,12);
if m_act == 0
m_act = 12;
end

%Accounts for extra data points from having more than one year.
for d_calc = 1:Months(m_calc)
row = 1;

%For 23 STMs, assuming the 24th (midnight) will be 0.
for h_trans = 1:24
if h_trans == 24

```

Figure A.8. Solar_Irradiation_Simulator.m (1/2)

```

Sol_Level(h_trans,d_calc,m_calc) = 0;
else
q = 0;
for j = 1:(Total_Maximum/10)+1
if A(h_trans,d_calc,m_calc)<BIG_cum_STM(m_act,h_trans,row,j) && q == 0
%The matrix starts at 0 W/m^2, i.e. 1/1 in the matrix corresponds to 0 W/m^2 transitioning to 0 W/m^2.
q = 1;
Sol_Level(h_trans,d_calc,m_calc) = (j-1)*10;
nextrow = j;
break;
end
end
end
row = nextrow;
end
end
end
%The data needs to be placed into a column vector and massaged to remove days that don't exist. (Not all
%months have 30 days!)
%Places into a column vector
z = reshape(Sol_Level,24*m_sim*31,1);
%Removes the extra day generated due to Leap year. (Not required with TMY3)
%z(8761:8784) = -1;
%Removes all rows where the value is equal to -1.
z(all(z==-1,2),:) = [];
%The STM approach yields data that is one hour off (i.e., data at 10 am is showing up at 9 am instead. This
%is because each day starts at midnight, not at 1 am. The column vector above will now be "shifted" down to
%ensure the estimated solar data shows up at the right time of the day.
s1 = size(z); %Size of the column vector
s2 = s1(1); %Number of datapoints
zshift = z(1:(s2-1));
first_point = 0; %Adds a zero at the beginning of the simulated data set.
Solar(:,tr) = cat(1,first_point,zshift); %The "shifted" set of solar data
end
end

```

Figure A.9. Solar_Irradiation_Simulator.m (2/2)

```

function [PV_Output, Total_PV_Generation] =
PV_Output_Calculator(Solar,Number_of_Trials,Solar_Panel_Range,Solar_Panel_Rating,PV_Derating_Factor)
%PV_Output_Calculator Takes the simulated solar data and solar panel information to determine the PV output
%for each solar panel configuration.

%Determines the number of configurations
Number_of_Configurations = size(Solar_Panel_Range,2);

%Initialize variable PV_output
PV_Output = zeros(8760,Number_of_Configurations,Number_of_Trials);
Total_PV_Generation = zeros(Number_of_Configurations,Number_of_Trials);

for Trial_Number = 1:Number_of_Trials
    for Configuration_Number = 1:Number_of_Configurations
        for Hour = 1:8760
            Configuration = Solar_Panel_Range(Configuration_Number);
            PV_Output(Hour,Configuration_Number,Trial_Number) =
            PV_Derating_Factor*Solar(Hour,Trial_Number)/1000*Configuration*Solar_Panel_Rating/1000;
            %Sohttps://www.homerenergy.com/products/pro/docs/3.11/how_homer_calculates_the_pv_array_power_output.html
            Total_PV_Generation(Configuration_Number,Trial_Number) =
            Total_PV_Generation(Configuration_Number,Trial_Number) + PV_Output(Hour,Configuration_Number,Trial_Number);
        end
    end
end
end
end

```

Figure A.10. PV_Output_Calculator.m

```

function [Hourly_Load, Shared_Hourly_Load] =
Load_Demand_Simulator(Number_of_trials,Simulation_years,Load_Data)
%LOAD_DEMAND_SIMULATOR
% Load demand is simulated once for each SAPV system based on typical
% residential load profile.

%Number of SAPV Systems
Number_of_SAPV_Systems = size(Load_Data,2);

%Initialize variable Hourly_Load which will be output
Hourly_Load = zeros(8760*Simulation_years,Number_of_SAPV_Systems,Number_of_trials);
Shared_Hourly_Load = zeros(8760*Simulation_years,Number_of_trials);
%Initialize variable datapoints, similarly to
%Solar_Irradiation_Cum_STM_Generator.
datapoints = 0;

%Populates the variable Hourly_Load with historical data
for trial = 1:Number_of_trials
    for year = 1:Simulation_years
        for day_number = 1:365
            for hour_number = 1:24
                datapoints = datapoints +1;
                for system = 1:Number_of_SAPV_Systems
                    Hourly_Load(datapoints+8760*(year-1),system,trial) =
round(Load_Data(datapoints,system,trial),3);
                    Shared_Hourly_Load(datapoints+8760*(year-1),trial) =
Shared_Hourly_Load(datapoints+8760*(year-1),trial) + Hourly_Load(datapoints+8760*(year-1),system,trial);
                end
            end
        end
    end
    datapoints = 0;
end
end
end

```

Figure A.11. Load_Demand_Simulator.m

```

function [Baseline_Table] =
Baseline_ESS_Analysis(Hourly_Load,PV_Output,Total_PV_Generation,Battery_Capac
ity,Battery_Efficiency,Initial_Battery,Solar_Panel_Range,Battery_Cost,Solar_P
anel_Cost,SAPV_Analysis,LPSF_Count)
%BASELINE ESS ANALYSIS
% Battery State of Charge (SOC) is calculated (every hour), if battery
% SOC exceeds 100% that energy is stored in energy excess array, if
% battery SOC breaks 0% the amount of energy not supplied is stored in
% energy deficit array.

fprintf('-----\n')
fprintf('          BASELINE ESS ANALYSIS\n')
fprintf('-----\n')

%Number of Configurations
Number_of_Configurations = size(PV_Output,2);

%Number of Trials
Number_of_Trials = size(PV_Output,3);

%Number of simulation hours
Simulation_Hours = size(Hourly_Load,1);

%Number of SAPV_Systems
Number_of_SAPV_Systems = size(Hourly_Load,2);

%Compares energy produced by solar panels with the load
Delta_Baseline=
zeros(Simulation_Hours,Number_of_SAPV_Systems,Number_of_Configurations,Number
_of_Trials);

%Variable gives amount of storage in battery at present time. Begins at
%full charge
Baseline_Battery_Stored =
zeros(Simulation_Hours,Number_of_SAPV_Systems,Number_of_Configurations,Number
_of_Trials);

%Used in iteration
Battery =
zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
Battery(:) = Initial_Battery;

%Counts how many hours you are fully charged (Loss of PV Generation) and
%how much solar power is unutilized. Used to calculate %PV Utilization.
LOPVG_Count =
zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
LOPVG_Loss =
zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
PV_Utilization =
zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);

%Declares cost variables so averages can be taken
Total_Solar_Panel_Cost =
zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);

```

Figure A.12. Baseline_ESS_Analysis.m (1/5)


```

Total_Battery_Cost =
zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
Capital_Cost =
zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);

%Initializes variables which will be used to take the average of all
%systems
Average_Battery = zeros(Number_of_Configurations,Number_of_SAPV_Systems);
Average_LOPVG_count = zeros(Number_of_Configurations,Number_of_SAPV_Systems);
Average_LOPVG_loss = zeros(Number_of_Configurations,Number_of_SAPV_Systems);
Average_PV_Utilization =
zeros(Number_of_Configurations,Number_of_SAPV_Systems);
Average_Panel_Cost = zeros(Number_of_Configurations,Number_of_SAPV_Systems);
Average_Battery_Cost =
zeros(Number_of_Configurations,Number_of_SAPV_Systems);
Average_Capital_Cost =
zeros(Number_of_Configurations,Number_of_SAPV_Systems);

%Initializes excel file to store data so it's not done on every iteration.
%SAPV_Analysis = 'SAPV_Analysis.xlsx';
excel_datapoint = 1;

%Initializes array for use in writing to excel file. xlswrite is slow!
total_datapoints = Number_of_Trials * Number_of_Configurations;
Baseline_Table = zeros(total_datapoints,12,Number_of_SAPV_Systems);

for configuration = 1:Number_of_Configurations
for trial = 1:Number_of_Trials
for system = 1:Number_of_SAPV_Systems

%Variable solved indicates when reliability requirement met
solved = 0;

while solved == 0

%Energy Deficit Array. Counts how many hours you are fully discharged%(Loss
%of Storage) and how much energy is lacking. Used to calculate LPSP.
LOS_count = 0;
LOS_lack = 0;

for hour = 1:Simulation_Hours
Delta_baseline(hour,system,configuration,trial) =
PV_Output(hour,configuration,trial)-Hourly_Load(hour,system,trial);
if hour == 1
Baseline_Battery_Stored(hour,system,configuration,trial) =
0.5*Battery(configuration,trial,system)*Battery_Capacity; %Battery not
shipped fully charged!
else if Delta_baseline(hour-1,system,configuration,trial)<0
%Battery Efficiency only considered when charging

Baseline_Battery_Stored(hour,system,configuration,trial)=max(Baseline_Battery
_Stored(hour-1,system,configuration,trial)+Delta_baseline(hour-
1,system,configuration,trial),0);

```

Figure A.13. Baseline_ESS_Analysis.m (2/5)

```

=== 0
      if Baseline_Battery_Stored(hour,system,configuration,trial)
          LOS_count = LOS_count +1;
          LOS_lack = LOS_lack + abs(Baseline_Battery_Stored(hour-
1,system,configuration,trial)+Delta_baseline(hour-
1,system,configuration,trial));
      else
          Baseline_Battery_Stored(hour,system,configuration,trial)=min(Baseline_Battery
_Stored(hour-
1,system,configuration,trial)+(Battery_Efficiency*Delta_baseline(hour-
1,system,configuration,trial),Battery(configuration,trial,system)*Battery_Ca
pacity);
          if Baseline_Battery_Stored(hour,system,configuration,trial)
=== Battery*Battery_Capacity-LOPVG_count(configuration,trial,system) =
LOPVG_count(configuration,trial,system) +1;
LOPVG_loss(configuration,trial,system) =
Delta_baseline(hour,system,configuration,trial);
      end
    end
  end

  if LOS_count <= LPSP_Count
      %Total_Energy_Storage =
Battery(configuration,trial,system)*Battery_Capacity;
      LPSP = (LOS_count/Simulation_Hours)*100;
      ((Total_PV_Generation(configuration,trial)-
LOPVG_loss(configuration,trial,system))/Total_PV_Generation(configuration,tri
al))*100;
      Total_Solar_Panel_Cost(configuration,trial,system) =
      (Solar_Panel_Range(configuration)*Solar_Panel_Cost);
      Battery(configuration,trial,system)*Battery_Cost =
      Battery(Capital_Cost(configuration,trial,system) +
      Total_Solar_Panel_Cost(configuration,trial,system) + Charge_Controller_Cost +
      Inverter_Cost;
      %-----
      %----- Used to save data to excel file
      %-----
      Baseline_Table(excel_datapoint,1,system) = trial;
      Baseline_Table(excel_datapoint,2,system) = trial;
      Solar_Panel_Range(configuration);
      Baseline_Table(excel_datapoint,3,system) =
      Battery(configuration,trial,system);
      Baseline_Table(excel_datapoint,4,system) = LOS_count;
      Baseline_Table(excel_datapoint,5,system) =
      LOPVG_count(configuration,trial,system);
      Baseline_Table(excel_datapoint,6,system) = LOS_lack;
      Baseline_Table(excel_datapoint,7,system) =
      LOPVG_loss(configuration,trial,system);
  end
end
end

```

Figure A.14. Baseline_ESS_Analysis.m (3/5)

```

Baseline_Table(excel_datapoint,8,system) = LPSP;
Baseline_Table(excel_datapoint,9,system) =
PV_Utilization(configuration,trial,system);
Baseline_Table(excel_datapoint,10,system) =
Total_Solar_Panel_Cost(configuration,trial,system);
Baseline_Table(excel_datapoint,11,system) =
Total_Battery_Cost(configuration,trial,system);
Baseline_Table(excel_datapoint,12,system) =
Capital_Cost(configuration,trial,system);
%=====
else
Battery(configuration,trial,system) =
Battery(configuration,trial,system) +1; %Else the number of batteries does
not meet the LPSP requirement.
end
end
excel_datapoint = excel_datapoint + 1;
end
end
%Writes to the excel file outside of 'For' loop to speed up process.
Column_Names = {'Trial Number','Solar Panels','Batteries','LOS Count','LOPVG
Count','Loss of Supply (kWh)','LOPVG (kWh)','LPSP','PV Utilization','Total
Solar Panel Cost','Total Battery Cost','Capital Cost'};
xlswrite(SAPV_Analysis,Column_Names,'Baseline','A1');
xlswrite3(SAPV_Analysis,Baseline_Table,'Baseline','A2',1)

%Finds averages of desired values for each system in order to simplify data
manipulation
Averages_datapoints = Number_of_Configurations * Number_of_SAPV_Systems;
Table_Averages_Baseline = zeros(Averages_datapoints,9);
datapoint = 0;
for system = 1:Number_of_SAPV_Systems
configuration = 1:Number_of_Configurations
datapoint = datapoint +1;
Table_Averages_Baseline(datapoint,1) = system;
Table_Average_Baseline(datapoint,2) =
Solar_Panel_Range(configuration);
mean(Battery_Averages_Baseline(datapoint,3)) =
mean(Battery_Averages_Baseline(datapoint,4)) =
mean(LOPVG_count(configuration,:system));
mean(LOPVG_loss(configuration,:system));
mean(PV_Utilization(configuration,:system));
mean(Total_Solar_Panel_Cost(configuration,:system));
mean(Total_Battery_Cost(configuration,:system));
mean(Capital_Cost(configuration,:system));

```

Figure A.15. Baseline_ESS_Analysis.m (4/5)

```

Average_Battery(configuration, system) =
mean (Battery(configuration, : , system));
Average_LOPVG_count(configuration, system) =
mean (LOPVG_count(configuration, : , system));
Average_LOPVG_loss(configuration, system) =
mean (LOPVG_loss(configuration, : , system));
Average_PV_Utilization(configuration, system) =
mean (PV_Utilization(configuration, : , system));
Average_Panel_Cost(configuration, system) =
mean (Total_Solar_Panel_Cost(configuration, : , system));
Average_Battery_Cost(configuration, system) =
mean (Total_Battery_Cost(configuration, : , system));
Average_Capital_Cost(configuration, system) =
mean (Capital_Cost(configuration, : , system));
end

%Writes to the excel file outside of 'For' loop to speed up process.
Column_Names_Averages = {'System', 'Solar Panels', 'Average Batteries', 'Average
LOPVG Count', 'Average LOPVG Loss', 'Average PV Utilization', 'Average Cost for
Solar Panels', 'Average Cost for Batteries', 'Average Capital Cost'};
xlswrite('SAPV_Analysis', Column_Names_Averages, 'Baseline', 'N1');
xlswrite('SAPV_Analysis', Table_Averages_Baseline, 'Baseline', 'N2');

%Finds averages of desired values for every system in order to simplify data
manipulation
Average_Systems_datapoints = Number_of_Configurations;
Table_Systems_Baseline = zeros(Average_Systems_datapoints, 8);
datapoint = 0;

for configuration = 1: Number_of_Configurations
    datapoint = datapoint + 1;
    Table_Systems_Baseline(datapoint, 1) =
    Solar_Panel_Range(configuration);
    Table_Systems_Baseline(datapoint, 2) =
    mean(Average_Battery(configuration, :));
    Table_Systems_Baseline(datapoint, 3) =
    mean(Average_LOPVG_count(configuration, :));
    Table_Systems_Baseline(datapoint, 4) =
    mean(Average_LOPVG_loss(configuration, :));
    Table_Systems_Baseline(datapoint, 5) =
    mean(Average_PV_Utilization(configuration, :));
    Table_Systems_Baseline(datapoint, 6) =
    mean(Average_Panel_Cost(configuration, :));
    Table_Systems_Baseline(datapoint, 7) =
    mean(Average_Battery_Cost(configuration, :));
    Table_Systems_Baseline(datapoint, 8) =
    mean(Average_Capital_Cost(configuration, :));
end
%Writes to the excel file outside of 'For' loop to speed up process.
Column_Names_Systems = {'Solar Panels', 'Average Batteries', 'Average LOPVG
Count', 'Average LOPVG Loss', 'Average PV Utilization', 'Average Cost for Solar
Panels', 'Average Cost for Batteries', 'Average Capital Cost'};
xlswrite('SAPV_Analysis', Column_Names_Systems, 'Baseline', 'X1');
xlswrite('SAPV_Analysis', Table_Systems_Baseline, 'Baseline', 'X2');
end

```

Figure A.16. Baseline_ESS_Analysis.m (5/5)

```

function [Central_Table] =
Central_ESS_Analysis(Number_of_SAPV_Systems,Shared_Hourly_Load,PV_Output,Total_PV_Generation,
Battery_Capacity,Battery_Efficiency,Initial_Panel_Range,Solar_Panel_Cost,Battery_Cost,Solar_Panel_Cost,
SAPV_Analysis,LPSP_Count)
%CENTRAL_ESS_ANALYSIS
% Acts as one SAPV system with combined loads and PV output. Calculates
% difference in storage and load, battery required and capital cost.

fprintf('=====\n')
fprintf('          CENTRAL ESS ANALYSIS\n')
fprintf('=====\n')

%Number of Configurations
Number_of_Configurations = size(PV_Output,2);

%Number of Trials
Number_of_Trials = size(PV_Output,3);

%Number of simulation hours
Simulation_Hours = size(Shared_Hourly_Load,1);

%Converts PV_output and Total_PV_Generation to scenario with shared storage
Shared_PV_Output = PV_Output * Number_of_SAPV_Systems;
Shared_Total_PV_Generation = Total_PV_Generation * Number_of_SAPV_Systems;

%Compares energy produced by solar panels with the load
Delta_Central = zeros(Simulation_Hours,Number_of_Configurations,Number_of_Trials);

%Variable gives amount of storage in battery at present time. Begins at
%full charge
Central_Battery_Stored_kWh = zeros(Simulation_Hours,Number_of_Configurations,Number_of_Trials);

%Used in iteration
Shared_Battery = Initial_Battery;

%Variable to count how many hours you are fully charged (Loss of PV
%Generation) and how much solar power is unutilized. Used to calculate %PV
%Utilization.
LOPVG_count_central = zeros(Number_of_Configurations,Number_of_Trials);

```

Figure A.17. Central_ESS_Analysis.m (1/5)

```

LOPVG_loss_central = zeros(Number_of_Configurations,Number_of_Trials);

%Initializes variables for use in tables
Average_Battery_Shared = zeros(Number_of_Configurations,Number_of_Trials);
Average_Solar_Panels = zeros(Number_of_Configurations,Number_of_Trials);
PV_Utilization_central = zeros(Number_of_Configurations,Number_of_Trials);
Total_Solar_Panel_Cost = zeros(Number_of_Configurations,Number_of_Trials);
Total_Battery_Cost = zeros(Number_of_Configurations,Number_of_Trials);
Total_Capital_Cost_central = zeros(Number_of_Configurations,Number_of_Trials);
Solar_Panel_Cost_per_System = zeros(Number_of_Configurations,Number_of_Trials);
Battery_Cost_per_System = zeros(Number_of_Configurations,Number_of_Trials);
Capital_Cost_per_System = zeros(Number_of_Configurations,Number_of_Trials);

%Initializes excel file to store data so it's not done on every iteration.
%SAPV_Analysis = 'SAPV_Analysis.xlsx';
excel_datapoint = 0;

%Initializes array for use in writing to excel file. xlswrite is slow!
total_datapoints = Number_of_Trials * Number_of_Configurations;
Central_Table = zeros(total_datapoints,17);

for configuration = 1:Number_of_Configurations
    for trial = 1:Number_of_Trials

%Variable solved indicates when reliability requirement met
solved = 0;

while solved == 0

%Energy Deficit Array. Counts how many hours you are fully discharged(Loss
%of Storage) and how much energy is lacking. Used to calculate LPSP.
    LOS_count_central = 0;
    LOS_lack_central = 0;

    for hour_central = 1:Simulation_Hours
        Delta_Central(hour_central,configuration,trial) =
        Shared_PV_Output(hour_central,configuration,trial)-Shared_Hourly_Load(hour_central,trial);
        if hour_central == 1

```

Figure A.18. Central_ESS_Analysis.m (2/5)

```

Central_Battery_Stored_kWh(hour_central,configuration,trial) =
0.5*Shared_Battery*Battery_Capacity; %Battery not fully charged initially!!
else
    if Delta_Central(hour_central,configuration,trial)<0
        Central_Battery_Stored_kWh(hour_central,configuration,trial)=max(Central_Battery_Stored_kWh(hour_central-
1,configuration,trial)+Delta_Central(hour_central-1,configuration,trial),0);
        if Central_Battery_Stored_kWh(hour_central,configuration,trial) == 0
            LOS_count_central = LOS_count_central +1;
            LOS_lack_central = LOS_lack_central + abs(Central_Battery_Stored_kWh(hour_central-
1,configuration,trial)+Delta_Central(hour_central-1,configuration,trial));
        end
    else
        Central_Battery_Stored_kWh(hour_central,configuration,trial)=min(Central_Battery_Stored_kWh(hour_central-
1,configuration,trial)+(Battery_Efficiency*Delta_Central(hour_central,configuration,trial)),Shared_Battery*
Battery_Capacity);
        if Central_Battery_Stored_kWh(hour_central,configuration,trial) ==
Shared_Battery*Battery_Capacity
            LOPVG_count_central(configuration,trial) = LOPVG_count_central(configuration,trial) +
1;
            LOPVG_loss_central(configuration,trial) = LOPVG_loss_central(configuration,trial) +
Delta_Central(hour_central,configuration,trial);
        end
    end
end
end

if LOS_count_central <= LPSP_Count
    %Total_Energy_Storage_central = Shared_Battery*Battery_Capacity;
    Average_Battery_Shared(configuration,trial) = Shared_Battery/Number_of_SAPV_Systems;
    Total_Solar_Panels_Shared = Number_of_SAPV_Systems * Solar_Panel_Range(configuration);
    Average_Solar_Panels(configuration,trial) = Total_Solar_Panels_Shared/Number_of_SAPV_Systems;
    LPSP_central = (LOS_count_central/Simulation_Hours)*100;
    PV_Utilization_central(configuration,trial) = ((Shared_Total_PV_Generation(configuration,trial)-
LOPVG_loss_central(configuration,trial))/Shared_Total_PV_Generation(configuration,trial))*100;
    Total_Solar_Panel_Cost(configuration,trial) = Total_Solar_Panels_Shared*Solar_Panel_Cost;
    Total_Battery_Cost(configuration,trial) = Shared_Battery*Battery_Cost;
    Total_Capital_Cost_central(configuration,trial) = Total_Solar_Panel_Cost(configuration,trial) +
Total_Battery_Cost(configuration,trial); % + Charge_Controller_Cost + Inverter_Cost;

```

Figure A.19. Central_ESS_Analysis.m (3/5)

```

        Solar_Panel_Cost_per_System(configuration,trial) =
Total_Solar_Panel_Cost(configuration,trial)/Number_of_SAPV_Systems;
        Battery_Cost_per_System(configuration,trial) =
Total_Battery_Cost(configuration,trial)/Number_of_SAPV_Systems;
        Capital_Cost_per_System(configuration,trial) = Solar_Panel_Cost_per_System(configuration,trial) +
Battery_Cost_per_System(configuration,trial);
        excel_datapoint = excel_datapoint + 1;
        solved=1;
=====
%
%
%
Used to save data to excel file
=====
Central_Table(excel_datapoint,1) = trial;
Central_Table(excel_datapoint,2) = Total_Solar_Panels_Shared;
Central_Table(excel_datapoint,3) = Average_Solar_Panels(configuration,trial);
Central_Table(excel_datapoint,4) = Shared_Battery;
Central_Table(excel_datapoint,5) = Average_Battery_Shared(configuration,trial);
Central_Table(excel_datapoint,6) = IOS_count_central;
Central_Table(excel_datapoint,7) = IOPVG_count_central(configuration,trial);
Central_Table(excel_datapoint,8) = IOS_lack_central;
Central_Table(excel_datapoint,9) = IOPVG_loss_central(configuration,trial);
Central_Table(excel_datapoint,10) = IPSP_central;
Central_Table(excel_datapoint,11) = PV_Utilization_central(configuration,trial);
Central_Table(excel_datapoint,12) = Total_Solar_Panel_Cost(configuration,trial);
Central_Table(excel_datapoint,13) = Total_Battery_Cost(configuration,trial);
Central_Table(excel_datapoint,14) = Total_Capital_Cost_central(configuration,trial);
Central_Table(excel_datapoint,15) = Solar_Panel_Cost_per_System(configuration,trial);
Central_Table(excel_datapoint,16) = Battery_Cost_per_System(configuration,trial);
Central_Table(excel_datapoint,17) = Capital_Cost_per_System(configuration,trial);
=====
else
    Shared_Battery = Shared_Battery +1;
end
Shared_Battery = Initial_Battery;
end
end
%Writes to the excel file outside of 'For' loop to speed up process.

```

Figure A.20. Central_ESS_Analysis.m (4/5)


```

Column_Names = {'Trial Number', 'Total Solar Panels', 'Solar Panels per System', 'Total Batteries', 'Batteries
per System', 'LOS Count', 'LOPVG Count', 'Loss of Supply (kWh)', 'LOPVG (kWh)', 'LPSF', 'PV Utilization', 'Total
Solar Panel Cost', 'Total Battery Cost', 'Total Capital Cost', 'Solar Panel Cost per System', 'Battery Cost per
System', 'Capital Cost per System'};
xlswrite(SAPV_Analysis, Column_Names, 'Central', 'A1')
xlswrite(SAPV_Analysis, Central_Table, 'Central', 'A2')

%Finds averages of desired values in order to simplify data manipulation
Averages_datapoints = Number_of_Configurations;
Table_Averages_Baseline = zeros(Averages_datapoints,12);
datapoint = 0;

for configuration = 1:Number_of_Configurations
    datapoint = datapoint +1;
    Table_Averages_Baseline(datapoint,1) = Number_of_SAPV_Systems;
    Table_Averages_Baseline(datapoint,2) = mean(Average_Solar_Panels(configuration,:));
    Table_Averages_Baseline(datapoint,3) = mean(Average_Battery_Shared(configuration,:));
    Table_Averages_Baseline(datapoint,4) = mean(LOPVG_count(configuration,:));
    Table_Averages_Baseline(datapoint,5) = mean(LOPVG_loss_central(configuration,:));
    Table_Averages_Baseline(datapoint,6) = mean(PV_Utilization_central(configuration,:));
    Table_Averages_Baseline(datapoint,7) = mean(Total_Solar_Panel_Cost(configuration,:));
    Table_Averages_Baseline(datapoint,8) = mean(Total_Battery_Cost(configuration,:));
    Table_Averages_Baseline(datapoint,9) = mean(Total_Capital_Cost_central(configuration,:));
    Table_Averages_Baseline(datapoint,10) = mean(Solar_Panel_Cost_per_System(configuration,:));
    Table_Averages_Baseline(datapoint,11) = mean(Battery_Cost_per_System(configuration,:));
    Table_Averages_Baseline(datapoint,12) = mean(Capital_Cost_per_System(configuration,:));

end

%Writes to the excel file outside of 'For' loop to speed up process.
Column_Names_Averages = {'Number of Systems', 'Solar Panels per System', 'Battery per System', 'Average LOPVG
Count', 'Average LOPVG Loss', 'Average PV Utilization', 'Total Cost for Solar Panels', 'Total Cost for
Batteries', 'Total Capital Cost', 'Average Solar Panel Cost per System', 'Average Battery Cost per
System', 'Average Capital Cost per System'};
xlswrite(SAPV_Analysis, Column_Names_Averages, 'Central', 'S1')
xlswrite(SAPV_Analysis, Table_Averages_Baseline, 'Central', 'S2')

end

```

Figure A.21. Central_ESS_Analysis.m (5/5)

```

function [Table_IES]=IES_Analysis_N_Systems(Hourly_Load,PV_Output,Total_PV_Generation,Battery_Capacity,
Battery_Efficiency,Initial_Battery,Solar_Panel_Range,Battery_Cost,Solar_Panel_Cost,SAPV_Analysis,
LPSP_Count,Initial_Charge)
%IES_ANALYSIS
% Battery State of Charge (SOC) is calculated (every hour), if battery
% SOC exceeds 100% and no other system can take it that energy is stored
% in energy excess array, if battery SOC breaks 0% and no other system
% can sell it the amount of energy not supplied is stored in energy
% deficit array.

fprintf('-----\n')
fprintf(' IES ANALYSIS\n')
fprintf('-----\n')

%Number of Configurations
Number_of_Configurations = size(PV_Output,2);

%Number of Trials
Number_of_Trials = size(PV_Output,3);

%Number of simulation hours
Simulation_Hours = size(Hourly_Load,1);

%Number of SAPV Systems.
Number_of_SAPV_Systems = size(Hourly_Load,2);

%Compares energy produced by solar panels with the load
delta_IES= zeros(Simulation_Hours,Number_of_SAPV_Systems,Number_of_Configurations,Number_of_Trials);

%Variable gives amount of storage in battery at present time. Begins at
%full charge
IES_Battery_Stored =
zeros(Simulation_Hours,Number_of_SAPV_Systems,Number_of_Configurations,Number_of_Trials);

%Used in iteration
Battery = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
Battery(:,) = Initial_Battery;

% Calculates Total Energy Storage, LPSP, PV Utilization and Capital

```

Figure A.22. IES_Analysis_N_Systems.m (1/8)

```

% Cost for every system
Total_Energy_Storage = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
LPSP = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
PV_Utilization = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
Total_Solar_Panel_Cost = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
Total_Battery_Cost = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
Capital_Cost = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);

%Variable to count how many hours you are fully charged (Loss of PV
%Generation) and how much solar power is unutilized. Used to calculate %PV
%Utilization.
LOPVG_count = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
LOPVG_loss = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);

%Variable to count how many times a system buys energy when it is empty and
%sells energy when it is full
System_Buy = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
System_Sell = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);

%Variable to count how many times a system buys energy when it is not empty and
%sells energy when it is not full
System_Buy_NotEMPTY = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);
System_Sell_NotFULL = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);

%Variable counts the total trades by all systems
Total_Trade = zeros(Number_of_Configurations,Number_of_Trials);

%Initializes variables which will be used to take the average of all
%systems
Average_Battery = zeros(Number_of_Configurations,Number_of_SAPV_Systems);
Average_LOPVG_count = zeros(Number_of_Configurations,Number_of_SAPV_Systems);
Average_LOPVG_loss = zeros(Number_of_Configurations,Number_of_SAPV_Systems);
Average_PV_Utilization = zeros(Number_of_Configurations,Number_of_SAPV_Systems);
Average_Panel_Cost = zeros(Number_of_Configurations,Number_of_SAPV_Systems);
Average_Battery_Cost = zeros(Number_of_Configurations,Number_of_SAPV_Systems);
Average_Capital_Cost = zeros(Number_of_Configurations,Number_of_SAPV_Systems);

%Energy Deficit Array. Counts how many hours you are fully discharged%(Loss
%of Storage) and how much energy is lacking. Used to calculate LPSP.
LOS_count = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);

```

Figure A.23. IES_Analysis_N_Systems.m (2/8)

```

LOS_lack = zeros(Number_of_Configurations,Number_of_Trials,Number_of_SAPV_Systems);

%Initializes excel file to store data so it's not done on every iteration.
%SAPV_Analysis = 'SAPV_Analysis.xlsx';
excel_datapoint = 0;

%Initializes array for use in writing to excel file. xlswrite is slow!
total_datapoints = Number_of_Trials * Number_of_Configurations;
Table_IES = zeros(total_datapoints,16,Number_of_SAPV_Systems);

for configuration = 1:Number_of_Configurations
    for trial = 1:Number_of_Trials

%Variable solved indicates when reliability requirement met
solved = 0;

while solved == 0

%Energy Deficit Array. Counts how many hours you are fully discharged%(Loss
%of Storage) and how much energy is lacking. Used to calculate LPSP.
LOS_count(configuration,trial,:) = 0;
LOS_lack(configuration,trial,:) = 0;

for hour = 1:Simulation_Hours
    for system = 1:Number_of_SAPV_Systems
        delta_IES(hour,system,configuration,trial) = PV_Output(hour,configuration,trial)-
        Hourly_Load(hour,system,trial);
    end
    if hour == 1
        for system = 1:Number_of_SAPV_Systems
            IES_Battery_Stored(hour,system,configuration,trial) =
            Initial_Charge*Battery(configuration,trial,system)*Battery_Capacity; %Battery not fully charged initially!!
        end
    else
        for system = 1:Number_of_SAPV_Systems
            if delta_IES(hour-1,system,configuration,trial) >= 0
                IES_Battery_Stored(hour,system,configuration,trial)=min(IES_Battery_Stored(hour-
                1,system,configuration,trial)+(Battery_Efficiency*delta_IES(hour-
                1,system,configuration,trial)), Battery(configuration,trial,system)*Battery_Capacity);
            end
        end
    end
end

```

Figure A.24. IES_Analysis_N_Systems.m (3/8)

```

else
    %Battery Efficiency only considered when charging
    IES_Battery_Stored(hour,system,configuration,trial)=max(IES_Battery_Stored(hour-
1,system,configuration,trial)+delta_IES(hour-1,system,configuration,trial),0);
end
end

%A system has no charge
for system = 1:Number_of_SAPV_Systems
    if IES_Battery_Stored(hour,system,configuration,trial)== 0

        %If no system can handle the trade, increment LOS_count and IOS_lack, otherwise find a
        %system to trade with, initiate the trade, and increment System_Buy and
        %System_Sell_NotFULL
        [Max_Value,Max_System] = max(IES_Battery_Stored(hour-1,configuration,trial));
        1,Max_System,configuration,trial)
        LOS_count(configuration,trial,system) = LOS_count(configuration,trial,system) +1;
        LOS_lack(configuration,trial,system) = LOS_lack(configuration,trial,system) +
        abs(IES_Battery_Stored(hour-1,system,configuration,trial)+delta_IES(hour-1,system,configuration,trial));
    else
        IES_Battery_Stored(hour,Max_System,configuration,trial) = Max_Value+delta_IES(hour-
1,system,configuration,trial)+delta_IES(hour-1,Max_System,configuration,trial);
        System_Buy(configuration,trial,system) = System_Buy(configuration,trial,system) +1;
        System_Sell_NotFULL(configuration,trial,Max_System) =
        Total_Trade(configuration,trial,Max_System) +1;
    end
end

%A system has full charge
for system = 1:Number_of_SAPV_Systems
    if IES_Battery_Stored(hour,system,configuration,trial) ==
Battery(configuration,trial,system)*Battery_Capacity

        %If no system can handle the trade, increment IOPVG_count and IOPVG_loss, otherwise find a
        %system to trade with, initiate the trade, and increment System_Sell and
        %System_Buy_NotEMPTY

```

Figure A.25. IES_Analysis_N_Systems.m (4/8)

```

[Min_Value,Min_System] = min(IES_Battery_Stored(hour-1, :, configuration, trial));
if (Min_Value + Battery_Efficiency*((delta_IES(hour-1, system, configuration, trial)+(delta_IES(hour-
1,Min_System, configuration, trial)))) >= Battery(Min_System)*Battery_Capacity
    LOPVG_count(configuration, trial, system) = LOPVG_count(configuration, trial, system) + 1;
    LOPVG_loss(configuration, trial, system) = LOPVG_loss(configuration, trial, system) +
delta_IES(hour, system, configuration, trial);
else
    IES_Battery_Stored(hour, Min_System, configuration, trial) = Min_Value +
Battery_Efficiency*((delta_IES(hour-1, system, configuration, trial)+(delta_IES(hour-
1,Min_System, configuration, trial)));
    System_Sell(configuration, trial, system) = System_Sell(configuration, trial, system) +1;
    System_Buy_NotEMPTY(configuration, trial, Min_System) =
System_Buy_NotEMPTY(configuration, trial, Min_System) +1;
    Total_Trade(configuration, trial) = Total_Trade(configuration, trial) + 1;
end
end
end
end
if LOS_count(configuration, trial, :) <= LPSP_Count %Success!
    excel_datapoint = excel_datapoint + 1;
    solved=1;
for system = 1:Number_of_SAPV_Systems
    Total_Energy_Storage(configuration, trial, system) =
Battery(configuration, trial, system)*Battery_Capacity;
    LPSP(configuration, trial, system) = (LOS_count(configuration, trial, system)/Simulation_Hours)*100;
    PV_Utilization(configuration, trial, system) = ((Total_PV_Generation(configuration, trial) -
LOPVG_loss(configuration, trial, system))/Total_PV_Generation(configuration, trial))*100;
    Total_Solar_Panel_Cost(configuration, trial, system) =
Solar_Panel_Range(configuration)*Solar_Panel_Cost;
    Total_Battery_Cost(configuration, trial, system) =
(Battery(configuration, trial, system)*Battery_Cost);
    Capital_Cost(configuration, trial, system) = Total_Solar_Panel_Cost(configuration, trial, system) +
Total_Battery_Cost(configuration, trial, system);
end
end

```

Figure A.26. IES_Analysis_N_Systems.m (5/8)

```

=====
% Used to save data to excel file
%
%=====
for system = 1:Number_of_SAPV_Systems
    Table_IES(excel_datapoint,1,system) = trial;
    Table_IES(excel_datapoint,2,system) = Solar_Panel_Range(configuration);
    Table_IES(excel_datapoint,3,system) = Battery(configuration,trial,system);
    Table_IES(excel_datapoint,4,system) = LOS_count(configuration,trial,system);
    Table_IES(excel_datapoint,5,system) = LOPVG_count(configuration,trial,system);
    Table_IES(excel_datapoint,6,system) = LOS_lack(configuration,trial,system);
    Table_IES(excel_datapoint,7,system) = LOPVG_loss(configuration,trial,system);
    Table_IES(excel_datapoint,8,system) = LPSP(configuration,trial,system);
    Table_IES(excel_datapoint,9,system) = PV_Utilization(configuration,trial,system);
    Table_IES(excel_datapoint,10,system) = Total_Solar_Panel_Cost(configuration,trial,system);
    Table_IES(excel_datapoint,11,system) = Total_Battery_Cost(configuration,trial,system);
    Table_IES(excel_datapoint,12,system) = Capital_Cost(configuration,trial,system);
    Table_IES(excel_datapoint,13,system) = System_Buy(configuration,trial,system);
    Table_IES(excel_datapoint,14,system) = System_Sell(configuration,trial,system);
    Table_IES(excel_datapoint,15,system) = System_Buy_NotEMPTY(configuration,trial,system);
    Table_IES(excel_datapoint,16,system) = System_Sell_NotFULL(configuration,trial,system);
end
%=====
end

%If the system did not meet reliability requirement, increment battery.
for system = 1:Number_of_SAPV_Systems
    if LOS_count(configuration,trial,system) > LPSP_Count
        Battery(configuration,trial,system) = Battery(configuration,trial,system) +1; %Else the number
    of batteries does not meet the LPSP requirement.
    end
end
end
end
end

%Writes to the excel file outside of 'For' loop to speed up process.
Column_Names = {'Trial Number','Solar Panels','Batteries','LOS Count','LOPVG Count','Loss of Supply
(kWh)','LOPVG (kWh)','LPSP','PV Utilization','Solar Panel Cost','Battery Cost','Capital
Cost','System_Buy','System_Sell','System_Buy_NotEMPTY','System_Sell_NotFULL'};
xlswrite(SAPV_Analysis,Column_Names,'IES','AI')

```

Figure A.27. IES_Analysis_N_Systems.m (6/8)

```

xlswrite3(SAPV_Analysis,Table_IES,'IES','A2',1)

%Finds averages of desired values for each system in order to simplify data manipulation
Averages_datapoints = Number_of_Configurations * Number_of_SAPV_Systems;
Table_Averages_IES = zeros(Averages_datapoints,9);
datapoint = 0;

for system = 1:Number_of_SAPV_Systems
for configuration = 1:Number_of_Configurations
datapoint = datapoint +1;
Table_Averages_IES(datapoint,1) = system;
Table_Averages_IES(datapoint,2) = Solar_Panel_Range(configuration);
Table_Averages_IES(datapoint,3) = mean(Battery(configuration,:),system);
Table_Averages_IES(datapoint,4) = mean(LOPVG_count(configuration,:),system);
Table_Averages_IES(datapoint,5) = mean(LOPVG_loss(configuration,:),system);
Table_Averages_IES(datapoint,6) = mean(PV_Utilization(configuration,:),system);
Table_Averages_IES(datapoint,7) = mean(Total_Solar_Panel_Cost(configuration,:),system);
Table_Averages_IES(datapoint,8) = mean(Total_Battery_Cost(configuration,:),system);
Table_Averages_IES(datapoint,9) = mean(Capital_Cost(configuration,:),system));

Average_Battery(configuration,system) = mean(Battery(configuration,:),system));
Average_LOPVG_count(configuration,system) = mean(LOPVG_count(configuration,:),system));
Average_LOPVG_loss(configuration,system) = mean(LOPVG_loss(configuration,:),system));
Average_PV_Utilization(configuration,system) = mean(PV_Utilization(configuration,:),system));
Average_Panel_Cost(configuration,system) = mean(Total_Solar_Panel_Cost(configuration,:),system));
Average_Battery_Cost(configuration,system) = mean(Total_Battery_Cost(configuration,:),system));
Average_Capital_Cost(configuration,system) = mean(Capital_Cost(configuration,:),system));

end

end

%Writes to the excel file outside of 'For' loop to speed up process.
Column_Names_Averages = {'System','Solar Panels','Average Batteries','Average LOPVG Count','Average LOPVG
Loss','Average PV Utilization','Average Cost for Solar Panels','Average Cost for Batteries','Average
Capital Cost'};
xlswrite(SAPV_Analysis,Column_Names_Averages,'IES','R1')
xlswrite(SAPV_Analysis,Table_Averages_IES,'IES','R2')

%Finds averages of desired values for every system in order to simplify data manipulation
Average_Systems_datapoints = Number_of_Configurations;
Table_Systems_IES = zeros(Average_Systems_datapoints,8);

```

Figure A.28. IES_Analysis_N_Systems.m (7/8)


```

datapoint = 0;

for configuration = 1:Number_of_Configurations
    datapoint = datapoint +1;
    Table_Systems_IES(datapoint,1) = Solar_Panel_Range(configuration);
    Table_Systems_IES(datapoint,2) = mean(Average_Battery(configuration,:));
    Table_Systems_IES(datapoint,3) = mean(Average_LOPVG_count(configuration,:));
    Table_Systems_IES(datapoint,4) = mean(Average_LOPVG_loss(configuration,:));
    Table_Systems_IES(datapoint,5) = mean(Average_PV_Utilization(configuration,:));
    Table_Systems_IES(datapoint,6) = mean(Average_Panel_Cost(configuration,:));
    Table_Systems_IES(datapoint,7) = mean(Average_Battery_Cost(configuration,:));
    Table_Systems_IES(datapoint,8) = mean(Average_Capital_Cost(configuration,:));
    Table_Systems_IES(datapoint,9) = mean(Total_Trade(configuration,:));

end

%Writes to the excel file outside of 'For' loop to speed up process.
Column_Names_Systems = {'Solar Panels', 'Average Batteries', 'Average LOPVG Count', 'Average LOPVG
Loss', 'Average PV Utilization', 'Average Cost for Solar Panels', 'Average Cost for Batteries', 'Average
Capital Cost', 'Total Trades'};
xlswrite(SAPV_Analysis,Column_Names_Systems, 'IES', 'AB1')
xlswrite(SAPV_Analysis,Table_Systems_IES, 'IES', 'AB2')

end

```

Figure A.29. IES_Analysis_N_Systems.m (8/8)