Evaluating Payback Period Calculation Methods for Photovoltaic Systems: A Practical and Parametric Comparison

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ABSTRACT

Photovoltaic (PV) systems are one of the most common types of renewable energy. A key incentive for PV use is its's ability to generate passive income/savings. The payback period is the number of years a system takes to offset its own cost. The accuracy and ease of estimating this value varies depending on the method used. This study investigates a range of payback models, including software and manual algebraic methods, to evaluate their practicality and accuracy, including their use of PV-related parameters. Methods are compared using a qualitative scale. Predicted energy output will be compared to data collected from a real PV system to determine accuracy. Accessibility is assessed based on ease of use and user requirements, including required skills. PV parameters tested include weather conditions, system degradation and panel angle. While software evaluation focuses on usability, parameters will be presented through the manual calculations. This is because the primary concern for the software is its ease of use; meanwhile, the manual method offers greater transparency and improved testing conditions for these calculations. Results showed that incorporating real weather data (solar irradiance), inflation and physical PV specifications produced outcomes that aligned with the observed data. Simpler models that ignored these factors tended to overpredict long-term energy output and savings, though they were easier to use and more practical for many users. Some users may still benefit from complex, more accurate models. This demonstrates the need for transparent, user-appropriate tools for PV system calculations and supports more informed decision-making for solar investments. It also highlights opportunities to improve current modelling practices across the renewable energy field.

CERTIFICATION OF THESIS

I David Sendy declare that the Thesis entitled "Evaluating Payback Period Calculation Methods for Photovoltaic Systems: A Practical and Parametric Comparison" is not more than 15,000 words in length including quotes and exclusive of tables, figures, appendices, and references. The thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

Date: 23/05/2025

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To my mother, who supported my studies since the beginning.

DEDICATION

To my father, rest in peace.

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ABBREVIATIONS

AI	Artificial Intelligence
BOM	Bureau of Meteorology
eQUEST	Quick Energy Simulation Tool
FiTs	Feed-in Tariffs
HOMER	Hybrid Optimisation of Multiple Energy Resources
HYBRID	Hybrid Power System Simulation Model
iGRHYSO	Intelligent Generator of Hybrid Systems Optimization
iHOGA	Improved Hybrid Optimization by Genetic Algorithms
INSEL	Integration of Simulation, Evaluation, and Layout
LGC	Large-scale generation certificate
ML	Machine Learning
NOCT	Nominal operating cell temperature
PC3D	Photovoltaic Concentrator 3D Simulation Software
PV	Photovoltaic
PVsyst	Photovoltaic System Software
QDSC	Quantum dot solar cell
RETScreen	Renewable-energy and Energy-efficiency Technology Screening software
SAM	System Advisor Model
STC	Standard test conditions
TPV	Thermophotovoltaic
TRNSYS	Transient System Simulation Tool
Voc	Open Circuit voltage

CHAPTER 1: INTRODUCTION

1.1. PV Payback Period

Photovoltaic (PV) is a major type of renewable energy system that converts solar irradiance from the sun into electricity using the photovoltaic effect and semiconducting materials (Fahrenbruch & Bube 2012; Benda & Černá 2020). As the technology and relevancy of these systems continue to grow, the use of PV has become of increasing interest to multiple stakeholders, including both private homeowners and large-scale energy companies. One concern that is often brought up is the financial gains and losses from using renewable energy, including PV (Delapedra-Silva et al. 2022). One of the simplest ways of displaying this dynamic is the payback period, which is defined as the amount of time required for a PV system to recover its initial cost through both saving resources and generating income from energy produced (Kagan 2024).

Different users benefit from calculating the payback period in various ways. A homeowner may be primarily interested in how long it will take for the rooftop system to pay for itself through reduced monthly electricity bills. In contrast, a business owner may be more focused on return on investment or decreasing operational costs over time. Engineers use the payback period to support system design, considering cost efficiency. Researchers and policymakers evaluate economic feasibility using payback calculations, either as a case study or to support policy decisions. Lastly, industry professionals often use these calculations in marketing or when presenting a system to a client. All these users need accurate and flexible methods to calculate the payback period to suit their requirements (O'Flaherty et al. 2012; Kessler 2017; Gorshkov et al. 2018; de Souza et al. 2019; Kohli et al. 2022).

Methods can be grouped into manual and software-based options. Manual methods require the user to gather data and apply mathematical techniques directly. This includes using basic equations that involve system costs, reported annual energy output, and electricity prices to test a system's feasibility quickly when software tools aren’t available. In contrast, software tools typically offer detailed simulations, energy predictions, degradation analysis, and other financial information to help estimate payback periods. However, the two methods vary in the skills and resources required. Manual methods can be challenging for those without data access, while using software may require extensive learning and often significant costs. Additionally, many popular software programs used in the PV industry and research do not focus on payback period calculations, leading to potential confusion with unrelated options that users may encounter (González-Peña et al. 2021; Milosavljević et al. 2022).

These methods all require a list of assumptions and parameters that significantly affect the results. This includes solar irradiance in the area, degradation, temperature effects and electricity rates (Lambert et al. 2006; Mahendra Lalwani 2010; Sinha & Chandel 2014). These factors need to be evaluated and tested, their importance also differs based on the system size, its geographical location and usage (Natural Resources Canada 2005; Blair et al. 2018). Therefore, some parameters may be more important to incorporate than others based on both the system and the user's preferences and needs. Understanding the importance of these factors and their impact on results is essential for accurate and useful analysis.

This research project aims to perform a qualitative study into the various modern payback period calculation methods and the importance of the factors involved. This includes the ability to apply PV specifications, weather data and any recent advances or changes in technology. The research question is:

"How do different payback period methods meet the practical needs of photovoltaic (PV) users?"

In addition to this general question, several sub-questions will be addressed, including:

- Do existing commercial payback models take into account recent advances in photovoltaic (PV) technology?
- Which assumptions and parameters have the greatest impact on the accuracy of payback period estimates?
- How do manual methods compare to software-based tools in terms of usability, accessibility, and complexity?
- Which user types (e.g., homeowners, engineers, researchers) benefit most from specific types of payback models?
- What limitations or trade-offs exist between model accuracy and simplicity?

This aims to focus on both the technical ability, both the likeliness to succeed and the accessibility of each tested method for a range of different PV users.

1.2. Scope of Study

This research focuses on small to medium scale PV systems such as those found in residential, commercial and institutional areas. The components are as follows:

- A literature review of the existing payback period methods, both manual and software based.
- Testing and evaluation of selected methods, covering a range of complex and accessible options.
- Qualitative analysis of each method's output, including payback period and details about the system itself.
- A discussion on the usability, complexity, and data requirements for each method.
- An investigation of key parameters and assumptions. Both their effects on payback period results and the ease with which they can be incorporated into each method.

Not included will be:

- Large-scale utility PV systems with advanced grid-tied behaviour or wholesale market modelling, these systems often have professionals who are trained to be able to evaluate all aspects including payback.
- Financial tools such as discounted cash flow (DCF), internal rate of return (IRR), or net present value (NPV). These are outside the practical scope for many small system users and add complexity not essential to the central research question.
- Policy-based or tax incentive modelling, these vary greatly based on region and data can be difficult to access for most private users.
- Extensive geographic modelling: instead, this study uses assumptions and available public data for solar irradiance and system characteristics and that is what most private users will inevitably use as well.

Many such exclusions must be made due to limited access to real-world data and time constraints. The focus is on general usability and therefore will focus on the more realistic methods people will use. Private users will likely also need to adhere to the same restrictions and scope.

1.3. Justification

As PV systems become more common and generally cheaper, the methods used to assess their economic feasibility efficiently is important (Fazal & Rubaiee 2023). A method needs to be accurate, but it must also be accessible and up to date. The output, degradation, and installation of PV modules vary and the resources to determine which of these factors need to be considered are lacking; therefore, a model based on outdated assumptions can result in inaccurate information about the financial outcomes of using PV (Krechowicz et al. 2022; Nguyen & Müsgens 2022).

The differing needs of users, including technical professionals and everyday consumers, mean that tools must be easy to use, accessible, and flexible in their methods. Therefore, it is important to periodically review the capabilities of existing payback models and assess whether they meet current requirements.

This project allows for further insight into the methods most used in PV research and in the industry at large. Comparing the tools used, the parameters that have the most significant impact on accuracy and the reliability of results. Finally, by examining the outputs and practical considerations of differing methods, the importance of transparency and simplicity will become clear. Is having an accessible, reliable, and user-controlled method still a central principle when making decisions on energy solutions?

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

This literature review will explore the research question: "How do different payback period methods meet the practical needs of photovoltaic (PV) users?" This inquiry is significant in the context of rapid technological advancement, as new developments can introduce a variety of parameters and factors that need to be carefully considered. Given these changes, it is essential to reassess and potentially update the calculation methods traditionally employed in these models.

In this review, we will examine the commonly used techniques for determining payback periods associated with PV technology. This will include a detailed discussion of the various factors that influence these calculations, such as installation costs, energy savings, maintenance requirements, and the impact of government incentives. It is vital for these factors to reflect the current state of technology to ensure that the models remain relevant and accurate. Different users vary in their need for the payback period; a homeowner requires a quick and straightforward answer to decide on their system. An engineer or analyst would require a more detailed analysis.

This literature review will provide a broad overview of payback period methods, and it will highlight some of the major factors that influence the results. It will review some of the available types of PV software and possible tools. This aims to help stakeholders in the renewable energy sector make better decisions.

2.1.1. Photovoltaics

PV cells convert heat or solar irradiance into electricity. They generate a small amount of energy, and a solar panel contains many of these cells, combined into a circuit, to provide usable amounts of electricity to the user. Brimblecombe and Rosemeier (2017) define a PV panel as layers of semiconductive material. PV systems produce energy steadily over time with relatively low maintenance, and the produced energy can be used directly, stored, or added to the grid (Al-Waeli et al. 2019).

The factors that affect the performance of PV energy systems over time are reviewed by Brimblecombe and Rosemeier (2017) and include degradation, temperature, solar irradiance, cloud coverage, type and size of the PV system, system setup and orientation, and peripheral devices such as solar trackers (Vyas et al. 2023).

The data used in these calculations is based on manufacturer ratings, which measure the performance of a PV model under standard test conditions involving 1000W/m^2 at 25°C. Manufacturers typically test for power output, efficiency, degradation rate, and temperature coefficient to gauge system performance under different temperatures. This data is crucial for assessing how the PV system will change with temperature variations and its impact on overall power production, especially for models designed for specific environments (Stein & Klise 2009; Dada & Popoola 2023).

To answer the research question, it is necessary to discuss software tools for renewable energy, payback period methods, and current developments in PV as of 2024. It will discuss the currently available software, the pros and cons, and its abilities to accurately calculate payback.

2.1.2. Importance of Payback Period in PV

Brenndorfer (1985) defines the payback period as the time it takes for a system's initial investment to be recouped through its operation. They suggest that the objective is not to recoup the initial cost but the profit that the system gains. Many authors, such as O'Flaherty et al. (2012); de Souza et al. (2019); Cohen (2024) give comprehensive discussions on these calculations. The calculations use data from the solar panel system provider, including initial cost, estimated performance, and projected savings. It determines the years needed for the cumulative cash flow to equal or exceed the initial cost. Software can be used for detailed analysis.

Typically, calculations for payback on a private house would use a model based on average performance in their region. Kagan (2024) gives an example where the system costs $5,000 and generates electricity worth $100 each month; the payback period would be 4.2 years. Another example is given by Farmer (2023) for a large solar farm where the payback could be 5-10 years for a $1,300,000 project producing $15,000 to $40,000 a year for each MW of power the farm produces and sells.

Homeowners would use information on the payback period to make an investment decision about their PV installation (Cucchiella et al. 2017). In this case they would mostly rely on the salesman to give them the calculations. Any calculations they would like to do themselves would need to be simple and user friendly. A different scenario would be an industry professional who would like to install a larger PV system, and the interest would need to be beneficial for their company (Barnard et al. 2021). In the case of the latter, the company has the capacity to hire a professional who would have the capability to use a more sophisticated payback analysis model.

2.1.3. Software Tools

Software tools assist users in completing various tasks quickly and easily. The user provides the software with values that describe the system, including system specifications, weather data, and the location and placement of the system. The software then uses an algorithm to determine the appropriate equation to simulate the system's energy output. Next, the user inputs any known financial information, and the software uses these data to calculate the payback period.

Sinha and Chandel (2014); Vashishtha et al. (2022) give overviews of software tools used in renewable energy, specifically hybrid systems involving solar. The ideal software can apply all assumptions, specifications, and data, and offers the flexibility of customisation. The varying methods that different software tools use are diverse and include determining a system's average performance, simulating the system's performance, estimating financial worth, assessing current financial worth, analysing weather data specific to different regions, and selecting appropriate solutions for various scenarios (Kazem et al. 2022). Software that analyses PV systems generally considers capacity, orientation, tilt, regional irradiance, performance ratios, and degradation rates over time (Man Yu 2015).

2.1.4. Overview of Existing Methods

A review by (Delapedra-Silva et al. 2022) discusses various methods for financial assessment, emphasising the importance of software tools for handling financial analysis in the field. Kohli et al. (2022) delves into using advanced software tools for financial analysis in the context of solar rooftop PV systems. Kohli et al. (2022) introduce real options analysis for identifying investment opportunities, providing risk management, and conducting value analysis for projects with high uncertainty and flexibility. The text also mentions the levelized cost of energy, which is a widely used metric for comparing the monetary value of different energy systems in hybrid systems (Martinez-Cesena & Mutale 2011; Gupta et al. 2020).

Machine learning (ML) and artificial intelligence (AI) are rapidly advancing technologies capable of independent analysis and prediction improvement (Nosratabadi et al. 2019; Kohli et al. 2022). Stochastic Modelling incorporates randomness, uncertainties, and probabilities to calculate payback under various outcomes (Awerbuch & Berger 2003). Hybrid methods combine techniques to enhance accuracy or provide multiple calculations, often by integrating elements from existing models. For example, Stochastic Modelling can be combined with other methods or integrated with machine learning and AI to improve the reliability of data used in calculations (Wang et al. 2019; Delapedra-Silva et al. 2022).

There are also different types of calculators that could be used, such as an omni calculator, multi-purposed financial calculators, excel-based calculators, hybrid simulators and AI/Machine learning-based calculators. Many websites, SolarReviews (SolarReviews 2024) and EnergySage (EnergySage 2024) for example, also provide online calculators which could be a good option for giving software adjacent tools to users who want a fast payback period calculation.

Domestic and business solar systems have distinct requirements. Businesses can engage skilled professionals for longer projects and often need larger systems for solar farms and factories. In contrast, domestic users focus on cost-effectiveness and clear guidance, typically opting for smaller systems with shorter payback periods (Dharshing 2017).

2.2. Review of Payback Period Methods

It is important to review traditional, non-software-based methods of calculating payback periods (Lefley 1996). There are many scenarios where a user may not have access to software or potentially don’t need to calculate data for renewable energy systems often enough to justify it (Raugei et al. 2012).

2.2.1. Pros and Cons of the Payback Period Model

The payback method has a drawback in that it does not account for the change in the value of money over time. It only considers cash inflows until the initial investment is recovered, disregarding any inflows and potential changes after this payback period (Lefley 1996). Manual methods can be used to calculate reasonable values, but they can be difficult when dealing with some of the complexities, such as changes in energy costs and system degradation. Software tools have the capacity to include a more extensive range of parameters but vary in their respective usability.

The main advantage of using a payback model is risk assessment by evaluating the financial risk of a long-term or short-term system (Gorshkov et al. 2018). It focuses on liquidity, emphasizing the recovery of liquid assets (money) and presenting the initial cost and the payback as raw cash. Additionally, it is important to calculate before starting a project, as it can be used as a tool to consider the success and validity of a single project or to help compare the risk of multiple projects (Delapedra-Silva et al. 2022)

One major disadvantage is the lack of information on changes in cash flow (Brenndorfer 1985). It may not reflect overall savings accurately. Most methods don't consider the time value of money or inflation, making it an inadequate metric for system profitability. Payback doesn't account for system lifespan, can be misleading for investors, and is less useful when comparing projects of different sizes. As a result, payback period results become more of a range than a specific value (Andrew et al. 2007).

Overall, the issues with the payback period can be resolved by conducting additional analyses. Many of the required values can be calculated using the system specifications as provided by the manufacturer, along with data and assumptions that have been made about the system. Implementing this using software would be straightforward, as most programs include databases that already provide these values and use built-in analyses (Short et al. 1995; Brealey et al. 2014; Damodaran 2014).

2.2.2. Assumptions and Physical Parameters

It's important to define the assumptions and parameters to calculate a value such as payback accurately (Stein & Klise 2009; Delapedra-Silva et al. 2022). The most important factors are the solar irradiance, initial investment, maintenance costs, annual cash flow, system lifespan and degradation. These are influenced by factors such as the type of PV, base material, and environmental conditions (Boyle 2012; Kohli et al. 2022). The initial investment also has an additional issue, such as the method of financing as either a cash purchase or loan investment.

Solar exposure is the most crucial factor in PV energy generation. Therefore, the location and placement of the panels are the most important considerations in the project. It is essential to use an energy model that incorporates location, as well as having access to climate databases (Sengupta et al. 2018). Another important consideration is to use an energy model that can allow for PV modules to lose efficiency over time due to degradation (Aghaei et al. 2022).

The electricity price is affected by inflation, and discounts for initial costs or annual savings may apply (Crismale 2024). The model must have consistent long-term performance that is affected by inflation and degradation, as well as fixed maintenance costs and accurate weather data (O'Shaughnessy et al. 2018). Energy costs are complex and highly dependent on the region and relevant market. Some markets are highly unsteady in their price changes (Delapedra-Silva et al. 2022).

It is necessary to account for any additional technology for the system. If the system is using solar trackers (Singh et al. 2018), the time the system is in direct sunlight would increase, but the amount of usage energy being generated per day would decrease.

Several factors, such as energy storage, environmental degradation, microclimate data, and electricity price changes, should be considered when evaluating the viability of renewable energy projects. Alsadi and Khatib (2018) notes that many analyses overlook important aspects such as maintenance costs, potential income from selling carbon offsets, and non-electricity benefits. Additionally, the likely increase in efficiency over time due to technological advancements is often not considered (Alsadi & Khatib 2018).

Different types of PV systems also require different data (see Table 2.1). Most software would be able to gather data for common types of PV, so the ability of a method to adjust for this is essential. To properly account for different types of PV, a model needs to access the temperature coefficient, efficiency, power output, average maintenance costs, degradation rate and initial costs (Sharma et al. 2018). The model may also assume that the proposed project will include any other factors that certain types of PV may have.

Table 2.1: Key factors specific to each system model, efficiency is the amount of energy that is converted to electricity, low = <10%, medium = 10% to 20%, and high is greater than 20%. Degradation is the loss of energy production, low indicates slow degradation of 25-30 years, medium degradation is between 10-20 years, high degradation is less than 10 years.

PV Technology	Efficiency	Cost Factors	Lifespan	Degradation	Other Factors	Payback Considerations
Crystalline Silicon (c-Si) [2,4,5,6,7]	High [4,5,6,7]	Decreasing cost. [5] Consistent mass production [7]	Long (25-30 years) [5]	Low [5,7]	Industry-standard, high availability [5]	Can be long due to high cost. [4] Short payback due to mature market and widespread adoption
Thin-Film [2,4,6,7] **(CdTe, CIGS, a-Si)**	Moderate [2,4,6,7]	Lower material costs, but installation can be complex [4,6,7]	Medium (20-25 years)	Moderate	It is flexible and suitable for use in unconventional spaces. High temperature tolerant. Cadmium is highly toxic. [2,4,6]	Longer payback in residential areas but good for large-scale installations
Dye-Sensitized Solar Cells (DSSC) [1,3,4]	Low [1,7]	Low-cost materials, but shorter lifespan [1,7]	Short (10-15 years) [1]	High [1]	Flexible, works in low-light conditions [3,4]	Payback highly dependent on location and application (e.g., indoor use)
Thermophotovoltaics (TPV) [2]	Moderate to High	High cost due to specialised technology	Long lifespan	Low	Waste heat can be used for power generation.	Payback is tied to specific industrial applications with available waste heat.
Organic PV (OPV) [3,4,7]	Low [3,7]	Very low-cost production but lower efficiency [4,7]	Short (5-10 years)	High	Lightweight, flexible, easily printable	Long payback due to shorter lifespan and low efficiency
Perovskite PV [3,4,7]	High (potential) [4,7]	Manufacturing still developing, potential for low costs	Medium	Still being researched	Promising, has potential for tandem cells	Could lead to very short payback periods if stability improves
Quantum Dot Solar Cells (QDSC) [3,4]	Low to Moderate [4]	Experimental, high current costs	Unknown (still developing)	Still being tested	Potential for integration in many devices	Payback period is uncertain due to technology maturity
Carbon Nanotube (CNT) [6]	Moderate to High	Expensive materials currently	Long	Low	High potential for flexible electronics	Could have short payback if production scales, but high initial costs
Hybrid PV Systems [2,6]	High [2,6]	Varies widely based on the types combined [2]	Long	Low to Moderate	Can combine high-efficiency PV with storage or concentrators	Payback depends on system configuration, with potential for short payback if optimised for specific environments

Sources: [1]Sharma et al. (2018); [2]Ahmad et al. (2020); [3]Dambhare et al. (2021); [4]Singh et al. (2021); [5]Ballif et al. (2022); [6]Dada & Popoola (2023); [7]Fazal & Rubaiee (2023)

2.2.3. Calculating Payback Period Without Using Software

Some users may want a simple payback estimation or only need to calculate payback once and don't want or need to commit to software. A financial consultant is one option due to their expertise in the industry. Academic, research, industry, and case study type resources all can provide a history of other PV systems in the same or similar regions with some comments and reviews on the performance, including payback period. It is also possible for those with analytical skills to do calculations using calculation software such as Excel, an option for those less concerned with accuracy.

Brenndorfer (1985) discusses ways to calculate payback using a formula with details on cash flow and rate of return. The most basic payback period calculation starts with the following formula as stated in Kagan (2024):

$$\text{Payback Period} = \frac{\text{Initial Investment}}{\text{Net Annual Cash Inflow}}$$

Boyle (2012) suggests a range of factors that contribute to the cost, suggesting ways to account for the change in cash flow rate (see Table 2.2). The initial cost includes materials and installation. The estimated energy produced per year is specific to the type of PV system used and maintenance and operational costs need to be accounted for to get the annual cash flow. The payback period is when the cumulative cash flow meets or exceeds the initial investment (Brenndorfer 1985; Kagan 2024).

2.2.4. Calculators Provided by Manufacturer/Company

Australian companies such as the National Solar Energy Group and Arise Solar offer various methods to calculate payback for their solar energy systems (Arise Solar 2022; Solarquotes 2024). These methods include utility programs that provide data and rates for selling the energy produced by a PV system back to the grid (Tushar et al. 2023). The programs estimate system performance based on similar systems in the area and offer a selling rate. A simple payback period can be calculated using this rate and the estimated performance. Companies often have websites, such as the one provided by Arise Solar (2022), where users can input primary data to get a rough payback period estimate. There are also solar communities where users can compare different solar plans and setups, providing a more social estimate of the system's value.

These methods use data directly from the manufacturer and utility company, making factors like initial and energy costs more accurate. However, they do not offer the specific or customisable options that some software might provide and are designed for casual, private users. They are often used as part of the sales process and may be biased, as they rely on data from other solar systems or assume optimal performance (Mickovic & Wouters 2020).

Table 2.2 presents a list of common factors that have an influence on the costs of the system that should be incorporated into the analysis of the payback period. Each factor has a specific impact on costs, such as an ongoing expense, an upfront expense or a long-term operational expense. The impact on revenue is an indication of whether the cost factor will influence the savings and/or income of the system, for example an upfront cost will have no impact on revenue and savings.

Table 2.2: Factors affecting costs and their relative impact on savings and expenses.

Factor	Impact on Costs (Expense)	Impact on Revenue (Savings/Income)	Notes
Installation Costs [1]	Increases upfront costs (labour, equipment, permits)	None directly	High initial expense influences overall system cost
Energy Produced [1,2,3]	None directly (maintenance may increase with energy production)	Reduces electricity bills or generates income from feed-in tariffs	More energy produced shortens the payback period
Maintenance [1]	Ongoing operational costs	None directly	Regular maintenance prolongs system lifespan but adds recurring costs
Inverter Replacement [1,4]	Increases costs (periodic expense)	None directly	Typically needs replacement every 10-15 years, a significant cost to factor in
Degradation Rate [1,3,4]	None directly	Reduces potential savings over time as energy production decreases	Higher degradation means less revenue from energy production over time
Government Incentives [1]	Reduces upfront or operational costs (grants, tax credits, rebates)	None directly (but incentivises installation)	Key to lowering payback time through subsidies or tax reductions
Feed-in Tariffs (FiTs) [2]	None directly	Generates revenue by selling excess energy back to the grid	Improves financial viability of the system, reducing payback time
Energy Storage (Batteries) [1,2,4]	Increases upfront costs	Can reduce electricity bills by optimising usage (charging during off-peak hours, discharging during peak hours)	High upfront and replacement costs, but can improve overall system performance
Land/Space Use	May incur additional costs (renting space, structural modifications)	None directly	Cost depends on location (rooftop, land purchase, etc.)
System Lifespan [3,4]	It affects long-term cost (replacement of system components)	Generates revenue over a longer time if lifespan is extended	Longer lifespan reduces the need for early replacement, maximising income potential

Sources: [1]Gupta et al. (2020); [2]Delapedra-Silva et al. (2022); [3]Fazal & Rubaiee (2023); [4]Cohen (2024)

2.3. Review of Software Tools in Renewable Energy

Several software packages exist for calculating payback and similar financial assessments. Sinha and Chandel (2014) present a review of software tools that automate routine tasks, offer customised outputs and reports, and are typically supported by customer service (Lalwani et al. 2010). PV technology evolves over time, which may necessitate new assumptions and parameters. Given the numerous options available, it is essential to provide a general overview of the PV system model of interest. This overview will help clarify the main ideas and facilitate a better understanding of the topic at hand. By outlining the fundamental aspects, better choices can be made to make informed decisions. Software-based methods allow better flexibility and precision when considering scenario modelling, long-term cash flow and risk analysis. One possible downside is that software can require a high level of technical skills (Vashishtha et al. 2022).

2.3.1. Common Software

The most used software programs for simulating renewable energy systems are Hybrid Optimisation of Multiple Energy Resources (HOMER) (Lambert et al. 2006), System Advisor Model (SAM) (Blair et al. 2018), and Renewable-energy and Energy-efficiency Technology Screening software (RETScreen) (Natural Resources Canada 2005). HOMER calculates payback by comparing different scenarios and optimising for cost, basing its assumptions, such as fuel price and resources, on any available performance in the area (Lambert et al. 2006). RETScreen calculates payback and completes feasibility studies using algorithms that can handle complex models and data to determine values and statistics based on the total initial cost, annual cost, and yearly savings and income (Natural Resources Canada 2005). SAM calculates payback based on realistic, nonconstant cash flow. An advantage of SAM is that it is possible to input detailed information (Blair et al. 2018). Detailed software features are described in Table 2.3.

Other standard software programs include Hybrid Power System Simulation Model (HYBRID), Improved Hybrid Optimization by Genetic Algorithms (iHOGA), Transient System Simulation Tool (TRNSYS), Intelligent Generator of Hybrid Systems Optimization (iGRHYSO), and Photovoltaic Concentrator 3D Simulation Software (PC3D) (Turcotte 2001; Stein & Klise 2009; Mahendra Lalwani 2010). These programs are capable of simulating hybrid systems and comparing different solutions. They provide access to data on manufacturing cost, capital cost, installation cost, and average performance for each system. Some software programs take a modular approach, allowing users to add or remove components to compare different configuration options. One software program, iHOGA, utilises a 'genetic algorithm' that selects all possible options for a renewable energy system and then eliminates until the best solution is found, similar to the process of natural selection (Sinha & Chandel 2014; Maheri 2021).

Software tools are varied, so it's crucial for users to consider their specific needs and priorities when choosing among them. Some offer extensive user bases, support services and continuous development (Bahramara et al. 2016), advanced system performance modelling and customizable system configurations (Blair et al. 2018). Tools that utilize climate data analysis and technology cost assessment are incredibly important in the renewable energy sector (Natural Resources Canada 2005). Climate data analysis examines weather patterns, temperature changes, sunlight, wind speeds, and other environmental factors. By understanding climate trends, these tools can find the best places for renewable energy projects. Technology cost assessment checks the financial side of renewable energy technologies. This includes costs for starting up, running, maintaining, and potential profits. Together, these tools are important for making sure renewable energy projects are both good for the environment and financially smart.

Some users prioritise the payback period, while others focus on factors such as energy production, environmental impact, versatility, and initial cost. Certain software tools can provide analysis using more than one objective, allowing users to select their preferences and quickly identify the best results (Kazem et al. 2022). They can also optimise systems that combine continuous and discrete data, conduct sensitivity analysis at a component level, and integrate financial models for taxes, loans, and cash flow using metrics such as internal rate of return and net present value (Arribas et al. 2011). Additionally, they can simulate off-grid and hybrid systems with battery storage, incorporate load profile inputs, and consider building integration. Furthermore, some emphasize grid interactions and offer 3D modelling capabilities, enabling users to customize module data (Dada & Popoola 2023).

Alsadi and Khatib (2018) reviewed several of the available software and identified the following key information (Table 2.3). HOMER is user-friendly and provides quick system comparisons but lacks consideration for financial factors like the change in the value of money over time and inflation. SAM attempts to account for the time value of money but overlooks long-term benefits after the payback period. RETScreen excels in financial analysis but is reliant on extensive user input. HYBRID is easy to use and quick to create designs but ignores long-term benefits after the payback period. iHOGA provides detailed solutions but is complex. TRNSYS offers detailed results but has a steep learning curve. iGRHYSO is simple to use but lacks long-term considerations, and PC3D overlooks long-term benefits and economic factors (Alsadi & Khatib 2018).

Table 2.3: Key features of software tools used for payback analysis. Complexity refers to the number of options that the system has available. Ease of use is defined for a user who is not a professional in the field of PV software, easy is no training, moderate is a small internet search and complex means some training required.

Software Tool	System Types Supported	Financial Model Complexity	Weather/Location Data	Energy Storage	Load & Demand Modelling	Hybrid Systems	Ease of Use	Unique Features
HOMER [1,3,4,5,7,8]	Off-grid, grid-tied, hybrid	Detailed, includes sensitivity analysis	Built-in global data	Yes	Yes	Yes	Moderate	Optimises for the most cost-effective design, incorporating both renewable and non-renewable systems.
SAM (System Advisor Model) [4,6,7,8]	Grid-tied, off-grid	Highly detailed, includes incentives and policies	NREL datasets can import weather files	Yes	Yes	No	Moderate to complex	Detailed financial and performance modelling for utility-scale projects
RETScreen [1,2,3,4,5,7,8]	Grid-tied, off-grid, hybrid	Basic to moderate	NASA weather data, local climate data	Yes	Yes	Yes	Easy	Includes benchmarking, energy efficiency, and GHG analysis; widely used for pre-feasibility
HYBRID [1,3,4,5,7]	Hybrid systems	Moderate	Built-in weather database	Yes	Yes	Yes	Moderate	Focuses on hybrid system integration, especially PV-diesel-battery configurations
iHOGA [5,8]	Off-grid, hybrid	Moderate, includes financing and economic analysis	External data input	Yes	Yes	Yes	Moderate	Designed for optimising off-grid systems with renewable sources and batteries
TRNSYS [1,4,5,7,8]	Hybrid, grid-tied	Complex, user-defined options	Customisable weather input	Yes	Yes	Yes	Complex	Simulation-focused, great for research and custom systems, requires expertise
iGRHYSO [5]	Hybrid, off-grid	Moderate to complex	External weather data	Yes	Yes	Yes	Moderate	Specialises in hybrid systems, focuses on rural electrification projects
PC3D [8]	Off-grid	Basic to moderate	External weather input	No	Yes	No	Easy	Simple, focused on educational use and small off-grid systems

Sources: [1]Turcotte (2001); [2]Natural Resources Canada (2005); [3]Lambert et al. (2006); [4]Stein & Klise (2009); [5]Sinha & Chandel (2014); [6]Blair et al. (2018); [7]Milosavljević et al. (2022); [8]Alsadi & Khatib (2018)

2.3.2. Other Software

There are also less common software packages that have methods that are unused by the more established software. One example is Integration of Simulation, Evaluation, and Layout (INSEL), which collects meteorological data to generate potential irradiance, temperature and humidity in selected regions (Sinha & Chandel 2014). Photovoltaic System Software (PVSyst) has a program that allows the user to input information on surrounding objects to estimate potential shading at various times of day (Kohli et al. 2022). Some software, such as the Quick Energy Simulation Tool (eQuest), uses step-by-step guides that guide the user to input the correct data (Xing et al. 2015). Some software has incorporated a marketplace, allowing users to compare provider quotes and prices.

There are also simple payback calculators. Many calculators exist on the internet, either on provider's websites or educational sources (Kazem et al. 2022). This often uses assumptions from the average of all PV systems across all regions to give a rough estimate of the payback period. While larger projects do not benefit from this, private users looking for a small PV system for their house can use this to approximate how long it will take to pay off their initial investment (Solar Bright 2022). This will typically be between 3-5 years and is used as a sales technique to get consumers to purchase solar panels.

2.4. Recent Developments

Different PV technologies also have an impact on calculation methods. New, developing technologies may one day become common enough that regular payback period analysis may need to be performed. It is important, therefore, to review the different types of PV.

The first-generation PV systems primarily use silicon, including monocrystalline, polycrystalline, amorphous, and ribbon silicon (Green 2003). These systems are standard, with lower production and market costs, average performance, and low degradation rates. These are the baseline for most PV-related studies and require minimal customisation in payback period calculations.

The second generation of PV technology includes various types of thin-film solar cells such as cadmium telluride, copper indium gallium selenide, and gallium arsenide (Dambhare et al. 2021). These systems generally have lower efficiency and shorter lifespans than first-generation systems but offer a better temperature coefficient and lower installation costs. Additionally, these technologies provide significant versatility, which may still be worth considering for users.

The third generation of PV includes new technologies such as dye-sensitised solar cells, thermophotovoltaics (TPV), organic PV, perovskite, Quantum Dot Solar Cell (QDSC), and carbon nanotubes (see Table 2.1) (Al-Waeli et al. 2019; Jarząbek & Jarząbek 2022; Lapotin et al. 2022; Dada & Popoola 2023). Each of these requires specific modifications for accurate payback period analysis. For example, thermophotovoltaics transfers heat, so precise temperature data is essential. At the same time, cloud coverage and the ratio of the measured output to the expected output are less critical (Lapotin et al. 2022). Some third-generation technologies offer advantages beyond performance such as improved efficiency, reduced costs and the use of novel materials, which affect payback period calculations (Sharma et al. 2018). Other technologies like organic PV and QDSC's are not widely used and have specific characteristics often not accounted for in standard calculators, such as tuneable spectral absorption in the case of quantum dot (Dada & Popoola 2023).

There are potential new developments that could lead to a fourth generation, such as hybrid systems (Turcotte 2001). Research is being conducted on the possibility of self-repairing and synthetic PV, which would also be considered fourth generation (Meng et al. 2021). It is unclear how these technologies will impact payback period calculations, but the existing model may eventually become inadequate for these new technologies.

2.5. Conclusion

In conclusion, most payback models can be updated to accommodate new PV systems technologies. The most crucial aspect influenced by PV technology is the overall power output, which directly impacts annual cash flow. If the model has access to weather/climate data and enables a prediction of power output that can estimate the change in power output over time, the payback model remains as valid as it was 10 years ago. Software technologies, AI, and machine learning have evolved, leading to enhanced modelling (Nosratabadi et al. 2019; Kohli et al. 2022). Additionally, a range of factors such as solar trackers and fixed tilt mechanisms, assumptions, and physical parameters can be incorporated to refine payback calculations. Manual calculations offer simplicity but are restricted in the amount of data they can use which can lead to a loss of accuracy. Software tools have better precision and can run many simulations in a short time frame but can be complex and require data inputs.

The payback period is important for assessing financial risk for renewable energy projects. After the payback period ends, the user can start saving money on electricity and making passive income (Karjalainen & Ahvenniemi 2019). To evaluate these projects correctly, it's important to understand the factors affected by technology and the environment. Software tools can help with the analysis, but users must choose options for their specific needs. As solar panel technologies improve, it's important to keep updating assessment models to reflect new performance data. Software methods are more capable of considering recent advances in PV technology due to customer feedback and the support staff.

There are several gaps in the current literature on software-based payback period calculations. There is no standardised method, this may lead to inconsistency and incomparable results. The complexity of using some of the software may lead to less accuracy due to a lack of understanding by the user. Static payback methods might be incapable of including updated market trends or technological advances.

The objective of this research is to investigate how different payback period methods meet the practical needs of PV users. Homeowners are generally only interested in paying off their system in a way that makes financial sense; they won't generally need to calculate it themselves. Researchers and Engineers, on the other hand, would benefit from this study because they need to incorporate a more sophisticated model to gain an in-depth understanding of their PV system and the relevant financial factors. The advantage of software tools is that they are constantly updated to include advances as needed, giving them a distinct advantage over manual methods. A PV system modelled on a real-life system will be used for analysis. The accompanying real-world data will be used to conduct tests on the models and determine the factors that have the most significant influence on the payback period.

CHAPTER 3: METHODOLOGY

3.1. Introduction

This chapter's content is organised into three sections: first, a detailed description of the data is provided; second, the equations used are explained; and finally, a comparison of the methods is conducted.

3.1.1. The Research Question

The research question is: "How do different payback period methods meet the practical needs of photovoltaic (PV) users?" Some of the more common methods of calculating the payback period will be used to determine the validity of using these methods' long term.

3.1.2. Approach

This research will use real data collected from a rural university in Queensland, Australia, employing software-based and manual analysis methods. A variety of assumptions and parameters will be considered and selected specifically due to the resources available for each testing method. After examining these methods, a comparative analysis will be conducted on the results. During this comparison, both the accuracy of each approach and the user experience based on the relative ease of obtaining results will be assessed. These evaluations are crucial for discussing the validity of the existing payback period methods, as they will provide insights into which method proves most effective and reliable in this context.

3.1.3. Scope

The study will clearly define its focus by identifying which payback period methods will be tested and the rationale for selecting them. Common software, HOMER, SAM and RETScreen will be tested as the standard examples of payback software. PC3D will be tested as an example of a method using macros, which are defined as a set of instructions that can be run using a single command. Manual methods that involve substituting values into mathematical equations will be used to verify and compare the results. The specific situations or contexts that these methods apply will be described.
Data Collection

3.1.4. Data Sources

Data used in this research is sourced from a rural university located in the southern region of Queensland, Australia. This includes power output, purchased electricity, cost and system specification for the "Solar Carpark."

Weather data from the Bureau of Meteorology, BOM (Bureau of Meteorology 2024), taken from a nearby weather station, was also used for comparison. These data include maximum, minimum and average temperatures, solar irradiance, and cloud cover. Data obtained from BOM are highly valuable and have been used in previous studies.

3.2. Available Data

The variables to be used in the calculations include the initial money spent to set up the system, ongoing expenses for maintenance and operation, the amount of energy the system is expected to generate and the total time the system is expected to last before it needs replacement or major repairs. The carpark data contains values for electricity used, measured in kilowatt-hours (kWh), every day from January 1, 2020, to August 31, 2024. This dataset also includes the day of the week for each usage record.

The solar panels that generate this electricity were constructed in 2017. The panels do not have solar trackers or tilt mechanisms. Information about whether the system has a fixed tilt was not acquired and could not be measured. Since they were first installed, no solar panels have been replaced or upgraded. The maintenance of the solar panel system has been limited. These panels follow the current convention of relying on rain to wash away dirt and debris.

3.2.1. Size of PV System

The carpark system contains 4037 panels manufactured by JinkoSolar Holdings Co Ltd JKM-285M-60 (Jinko Solar 2017). Table 3.1 lists the major components.

Table 3.1: Manufacturers Specifications for PV solar panels installed on the carpark (Jinko Solar 2017)

Solar Panel Brand	Jinko JKM285M-60
System Size	1090kW
Quantity of Panels	4037 x 270W
Cell Type	Mono-crystalline PERC (Passive Emitter and Rear Cell)
Number of cells	60
Dimensions (mm)	1650 x 992 x 40
Weight (kg)	19
Front Glass	3.2mm anti-reflection coating, High transmission, Low iron, Tempered glass
Frame	Anodised aluminium alloy
Junction Box	IP67 rated
Output cables	TUV 1x4mm^2, Length 900mm
Panel NOCT = 45 °C	45 °C
Temperature Coefficient (Pmax)	-0.37 / °C
Degradation	3%, linear degradation of 0.8% / year (based on the warranty)

3.2.2. Cost of the PV System

The university's initial cost totalled $3,825,935.20. This total covers the important expenses needed for the project to begin, such as designing resources, high-tech equipment and infrastructure (Table 3.2). No information was supplied for ongoing maintenance costs; therefore, we are assuming zero costs. This means we are not including regular upkeep, repairs, or support expenses that might arise during the project's duration.

Although financial details are important for transparency and planning, we do not have the exact split of funding between the government and the university. Estimates from the contractor about funding sources were not provided and therefore should be noted as a limitation.

Table 3.2 breaks down the costs to give a clearer view of the financial situation. Notably, $1.7 million is allocated for site preparation, which is crucial for setting up the groundwork for the project's future phases.

Table 3.2: Breakdown of the expenses for the Solar Carpark project.

Item	**Expense**
Carpark structure	$710,757.00
Micropiles	$273,827.28
HV installation Works	$264,768.75
Installation	$314,504.73
Engineering and Project Management	$25,652.91
Total including GST	$1,748,461.75
Modules	$929,918.16
Inverters	$215,424.68
External Protection	$47,070.00
Structural Engineering	$4,707.00
Data Monitoring	$7,320.41
Other Components	$173,935.51
Engineering and Project Management	$38,479.37
Installation	$471,757.10
Total including GST	$2,077,473.45
Total Cost of Project	**$3,825,935.20**

3.2.3. Continuous Costs

It has been advised that there have been no maintenance or repairs to the system.

3.2.4. Earnings

A Queensland electricity company, CS Energy, charges approximately $0.06 to $0.07 per kilowatt-hour (kWh). Demand charges also apply, which increases the effective cost per kWh by approximately 70%.

In addition, Large-scale Generation Certificates (LGCs) are created from eligible solar energy generation and can be sold at current market rates, typically ranging from $45 to $55 per megawatt-hour (MWh). An LGC is a tradable certificate issued under Australia's Renewable Energy Target scheme for every megawatt-hour of renewable electricity generated by an accredited large-scale power station (Clean Energy Regulator 2025). Monitoring electricity prices over time can help identify trends and account for inflation.

3.2.5. Known Parameters

It is important to use the same specifications if possible to enable the comparisons of the different methods. Table 3.3 shows the parameters that were specified by the project data manager.

Table 3.3: Known parameters used in all calculations

System Cost Assumed by all Methods	$3,825,935.20
Energy Output Assumed by all Methods	199.8 kWh/day
PV capacity	1090 kW
Inverter capacity	1140 kW
Electricity offset	$0.065 per kWh
LGC revenue	$50 per MWh ($0.05 per kWh)
System lifespan	25 years
Degradation	3%kW/year in year 1, linear decrease of 0.8%kW/year after
Electricity inflation	5%/year

3.2.6. Data Validation and Statistical Analyses

The data were assessed to ensure accuracy. They were compared to standards or benchmarks and also assessed using statistical methods. These techniques help to find any inconsistencies or errors. By applying these procedures, we can be satisfied that the data we work with is reliable and valid.

Statistical analyses were performed on the daily observations for temperature and solar irradiance to see how they affect the energy output from the car park. An analysis of variance was performed to test the significance of seasonal variation. A multiple linear model was used to assess the importance of each parameter to energy output.

The objective of testing various payback period methods is to evaluate their effectiveness in determining the time required for an investment to generate sufficient cash flows to recover its initial cost. Criteria include: the simplicity and ease of understanding of the method, the accuracy of the cash flow projections, the relevance of the method in different investment scenarios, and its ability to account for the time value of money. The goal is to clearly understand which payback period methods most accurately reflect the PV system that was used in the carpark data.

3.2.7. Software-Based Methods

Four software packages were used to simulate energy output and calculate a payback using the Jinko panels, as specified in Table 3.1. Full specifications for HOMER software can be found in Lambert et al. (2006). Instructions and screenshots are presented in Appendix A. The SAM software is fully described in National Renewable Energy Laboratory (2024). SAM opens with a menu that gives many options for the type of system; see Appendix B for details. The methods for using RETScreen are fully described in Natural Resources Canada (2005), see Appendix C for full details. PC3D is a simulator that uses Microsoft Excel (Basore 2020). Excel is a familiar, easy-to-use interface for specifying parameters and exploring the solution space (see Appendix D).

3.3. Calculations Using Manual Methods

Manual methods use known equations to calculate values by substituting the known factors. There are numerous ways of calculating payback. This section fully describes the equations for payback directly and uses equations to predict energy output, which in turn can be incorporated into a payback simulation.

The Carpark data includes costs, electricity prices and LGC revenue, therefore, a simple payback period can be calculated using the formula (Kagan 2024) as stated in section 2.2.3:

$$Payback\ Period\ = \frac{Total\ System\ Cost}{Annual\ Savings\ from\ Solar} \tag{3.1}$$

Using the System Cost from the Data collected as the Total System Cost. The car park data can also be used to estimate the energy generated in a year.

$$Annual\ energy\ generated = PV\ capacity\ \times capacity\ factor \times hours\ per\ year \tag{3.2}$$

Where the capacity factor is an estimated efficiency of the Jinko panels, given by 18.33% (Jinko Solar 2017).

Annual Savings can be calculated with:

$$Annual\ Savings = Annual\ Energy\ Output \times Total\ Value\ per\ kWh \tag{3.3}$$

The Total Value per kWh can be calculated by adding the Electrical Offset Value and LGC revenue provided in the data.

The carpark data and the system specifications will be used along with equations 3.1 to 3.5 to manually calculate the energy output and payback values to enable comparison with the software.

3.3.1. Calculations of Energy Prediction

The carpark data supplied provides, Energy output of the PV, Initial costs for payback and Temperature coefficient from the Jinko fact sheet (Jinko Solar 2017), see Table 3.1. The equations used as general underlying calculations followed by most software are presented in Riley et al. (2016). These equations are used in most software packages and can be modified to include sophisticated assumptions (Riley et al. 2016).

t = time (years)
D = degradation rate of PV system (% / year)
R = the rate increase in electricity costs (% / year)
P = the initial cost of the PV system upon installation ($)
I = the inflation rate of the dollar (% / year)
E_t = electrical energy generated by the system in year t (MWh)
C_t = the cost of electrical energy which is offset by the PV system in year t ($)
V_t = the value of the electrical energy offset by the PV system in year ***t*** ($). This is different than the cost C_t since the cost is in nominal year 1 dollars while the value is adjusted for inflation where, in general, future dollars are worth less than present dollars.

The energy generated in subsequent years must be reduced for degradation:

$$E_t = E_1\left[1 - \frac{D}{100}(t-1)\right] \qquad (3.4)$$

The cost of electricity that is offset by PV production for any year:

$$C_t = \left[C_1\left(1 + \frac{R}{100}\right)^{t-1}\right]E_t \qquad (3.5)$$

The value of the energy in year t:

$$V_t = C_t/\left[\left(1 + \frac{1}{100}\right)^{t-1}\right] \qquad (3.6)$$

Once the value of the energy offset in each year (Vt) is determined, the payback period can be calculated by determining the amount of time required for the cumulative value of the energy to exceed the initial cost of the PV system, i.e. the lowest value of n that satisfies:

$$\sum_{t=1}^{n} V_t \geq P \qquad (3.7)$$

The HOMER software uses the following equation to simulate PV solar energy as presented by Chisale et al. (2022). This equation incorporates solar irradiance and temperature variables.

$$PV_{poweroutput} = P_{\{pv,STC\}} f_{PV} \frac{G_T}{G_{\{T,STC\}}} [1 + K_P(T_c - T_{STC})] \tag{3.8}$$

Where:

$P_{\{pv,STC\}}$ is the photovoltaic array at peak power (kWp)

f_{PV} is the derating factor (%)

G_T is the solar irradiance striking the PV array (kW/m^2)

$G_{\{T,STC\}}$ is the solar irradiance under standard test conditions (1 kW/m^2)

K_P is the temperature coefficient of power (% / °C)

T_C is the photovoltaic temperature (°C)

T_{STC} is ambient temperature (25°C)

3.3.2. Adjusting for Panel Peripherals

The panels in the carpark data are known to have a tilt. It is important to adjust for this value. Tilting the panels will enable more of the surface area to be exposed to the sun, especially in winter months when the sun is lower. Figure 3.1 illustrates the calculations required to adjust the solar irradiance for solar panel tilt.

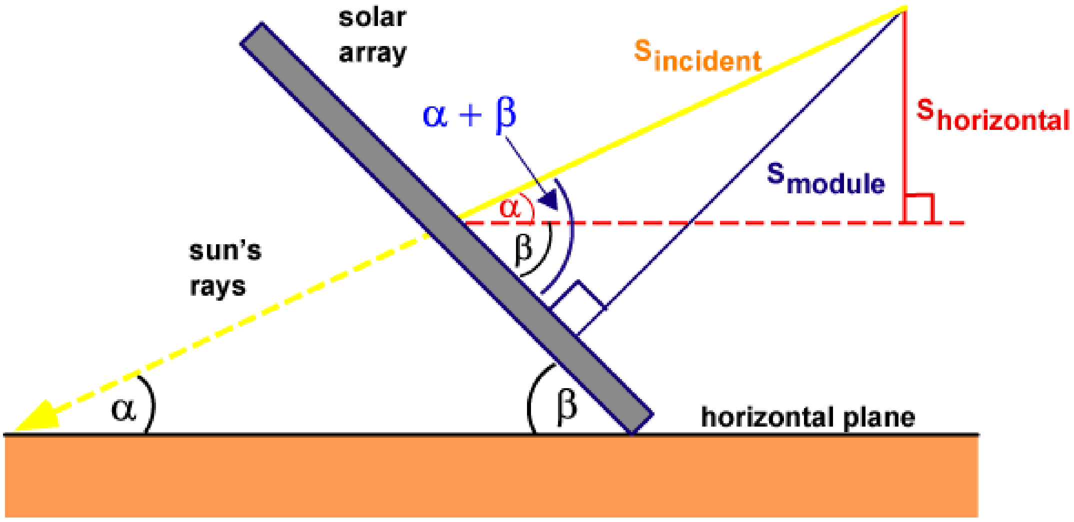

Figure 3.1: Diagram of tilt angle and its effect on irradiance
(Source: Honsberg and Bowden (2025))

The irradiance provided by BOM is represented in Figure 3.1 by $S_{horizontal}$. The tilt angle of the solar panel is represented in Figure 3.1 by β. S_{module}, the irradiance perpendicular to the panel is calculated by:

$$S_{module} = \frac{S_{horizontal} \sin(\alpha + \beta)}{\sin(\alpha)} \tag{3.9}$$

The angle of the sun $\alpha = 90 - \varphi + \delta$ where φ is the latitude and δ is the declination angle. The location of the carpark has a latitude of approximately 27.56°S, therefore the declination angle is given by Honsberg and Bowden (2025) as

$$\delta = 23.45^{\circ} \times \sin\left(\frac{360}{365} \times (d + 284)\right) \tag{3.10}$$

Where d is the day of the year (1,…,365).

The recommended tilt angle for latitudes above 20 is multiplied by 0.85 (Negro 2022).

3.4. Comparison Criteria

This study will present two different types of model comparisons: a quantitative comparison of the real-world carpark observed data against the results from manual models and software predictions. Secondly, the software types will be compared using qualitative analysis of complexity, usability, ease of use and software requirements.

3.4.1. Comparisons of the Carpark Data and the Software Output

The carpark energy data was compared to the predicted energy outputs from three different software packages and compared to values obtained by manual computation using the equations described below. Comparisons will be conducted between the carpark data and the degradation, temperature, solar irradiance, inflation and finally panel angle (tilt). Payback periods will then be found for each method and compared to the simple system specifications using a percentage error. For the degradation comparisons, the expected degradation from the system specifications will be shown against multiple years of carpark data and compared using a percentage error:

$$\%Error = 100 \times \left(\frac{Predicted\ value - actual\ value}{actual\ value}\right) \tag{3.11}$$

Finally, a linear regression will be fitted using long-term monthly weather data to predict values using each software type and the observed values against the baseline system spec model using a manual calculation.

$$Baseline\ energy = A + \beta.predicted\ energy + \epsilon \tag{3.12}$$

Where the *baseline energy* values are calculated manually using the system specifications, A is a constant that corresponds to the intercept, *the predicted energy* is the energy that has been calculated using software or the observed carpark energy, β is the gradient of the fitted line and finally ϵ is the residual.

Calculations were performed using statistical software R, and Microsoft Excel. The predicted energy output from the software was compared to the manual energy predictions. Different scenarios were accounted for by varying the equations.

3.4.2. Comparing Software Types

To answer the research question, a set of comparison criteria is presented in Table 3.4.

Accessibility is a subjective measure. Several key components can be considered. Firstly, the difficulty involved in installation and setup affects the user experience. Secondly, the learning curve includes such aspects as the clearness of the documentation and the intuitiveness of the user interface. Additionally, the amount of time it takes to generate meaningful results can impact the accessibility of a tool or system. Lastly, the required background knowledge, which may encompass fields such as engineering, finance, or modelling, further shapes an individual's ability to use the software.

The comparison of methods may include, but not exclusively:

- Accuracy, comparison with expected results using the system specifications.
- Complexity, the level of difficulty.
- Usability, how user-friendly was the software?
- Computational Requirements, amount of memory or calculation time.

There will also be an analysis of the assumptions and parameters, their effect on the results, ease of incorporation, and the required data.

- Temperature and solar irradiance and their role in the model.
- Degradation
- Energy Cost
- Panel orientation and tilt
- Shading and soil type
- Maintenance costs.

Table 3.4 Criteria for method comparison

Criterion	**Description**	**Measurement Approach**	**Justification/Notes**
Accuracy	How closely the output of the method aligns with the data collected from the solar carpark	Percentage error against the system spec value	Objective allows comparison based on data
Accessibility	Ease of use, availability and skill requirements	Qualitative examination based on user experience.	Subjective shows the real-world application of the methods
Input Requirements	Quantity and complexity of data inputs	Number of inputs and time/difficulty of collecting required information	Affects feasibility and limits the number of potential users
Cost	How available and costly are the tools required for the method	Free, requires a license or system requirements	Affects accessibility and the number of potential users
Parameters used	Does the method account for a variety of factors and the quality of the assumptions used	List of the available factors	Links to parameter evaluation

CHAPTER 4: RESULTS

4.1. Summary

The models tested include the software HOMER, SAM, RETScreen, PC3D and manual computational methods. The manual methods explore introducing different factors into the calculations such as degradation, temperature, solar irradiance and tilt angle. The methods were tested by entering values collected from a university PV system located in southern Queensland, Australia (referred to hereafter as "carpark data"). The aim is to answer the research question: "How do different payback period methods meet the practical needs of photovoltaic (PV) users?" The data itself will also be analysed to determine which parameters hold the most importance to calculating the payback period.

4.2. Statistical Analyses

The daily energy output from the carpark is plotted in Figure 4.1 along with the Maximum daily temperature and daily solar exposure as downloaded from BOM. Figure 4.1 shows that the energy generated by the car park, the maximum daily temperature, and the solar exposure all follow a sinusoidal pattern of high in the summer and low in the winter. The energy data show an unusual dip in early 2023 (in orange). This is an area that can be investigated. The energy and Solar Exposure data show a wider spread of values than the Temperature data, which appears to be tighter.

Monthly averages for each measurement are plotted in Figure 4.2, which shows that when using mean values for each month, the three measurements line up consistently.

Figure 4.3 shows high correlations between each of the three measurements. The lowest correlation is between Temperature and energy output; the area of difference that was noticed in Figure 4.1 is noticeable here, with the outliers visible in the Energy means. The correlation between Energy output and solar irradiance is very high (0.90), indicating that solar irradiance affects energy output more than temperature.

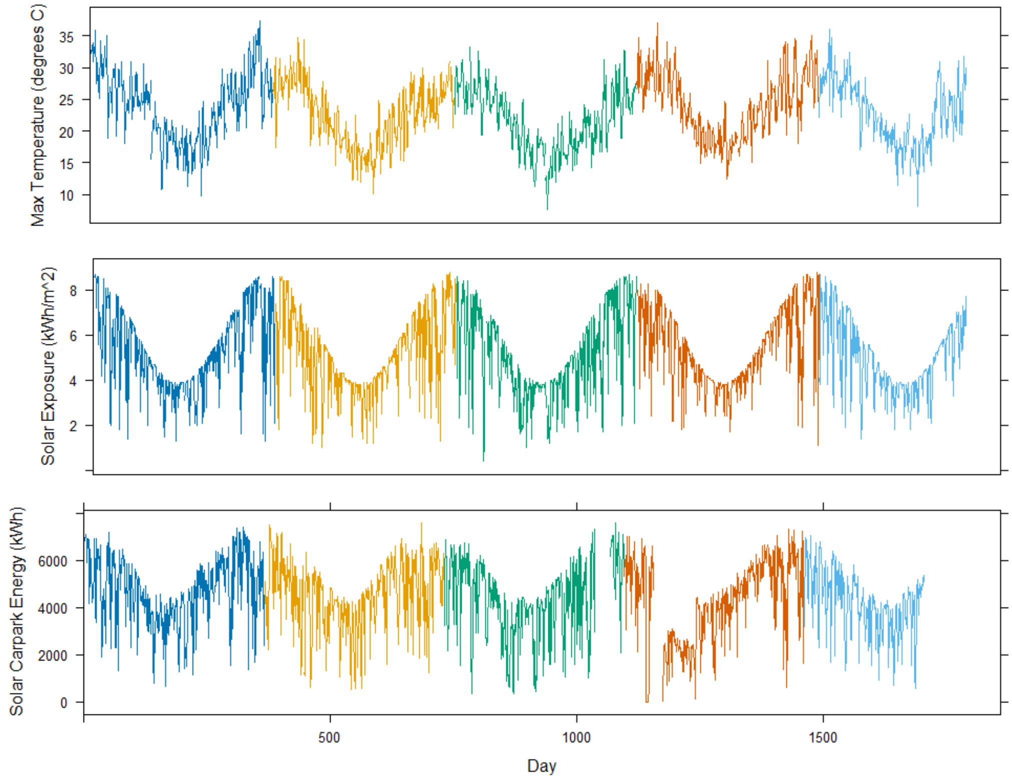

Figure 4.1: Daily measurements from 1/1/2020 to 31/8/2024 for energy and 1/1/2020 to 23/10/2024 for the temperature and solar exposure data; the colours represent years. The three measurements are: Top maximum daily temperature (°C); Middle: Solar Exposure (kWh/m^2); Bottom: Energy output from carpark data (kWh). Temperature and Solar exposure source (www.bom.gov.au).

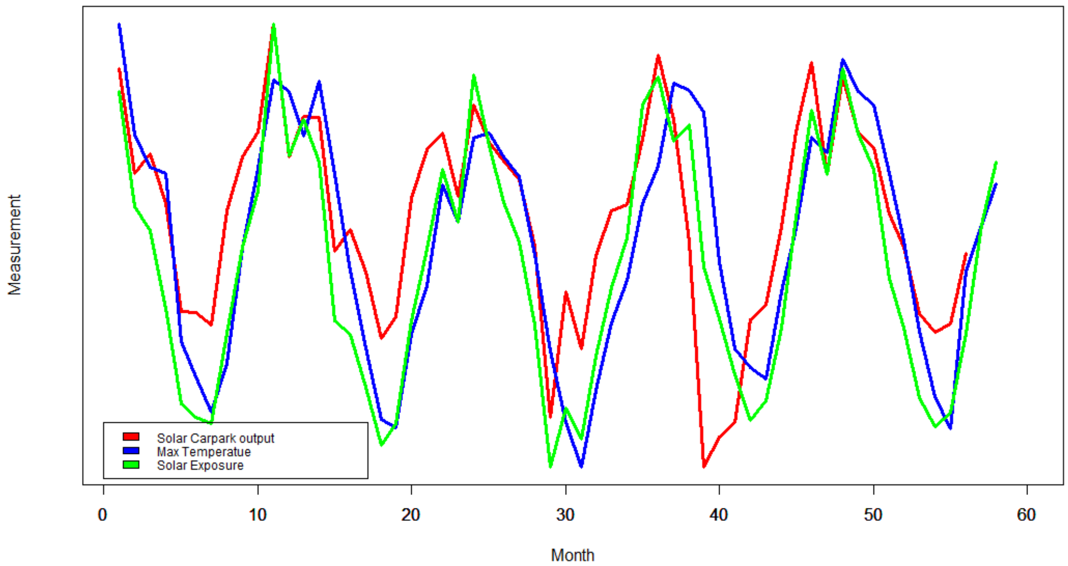

Figure 4.2: Monthly means for carpark output, Max Temperature and Solar Irradiance. The scale on the y axis is different for each measurement.

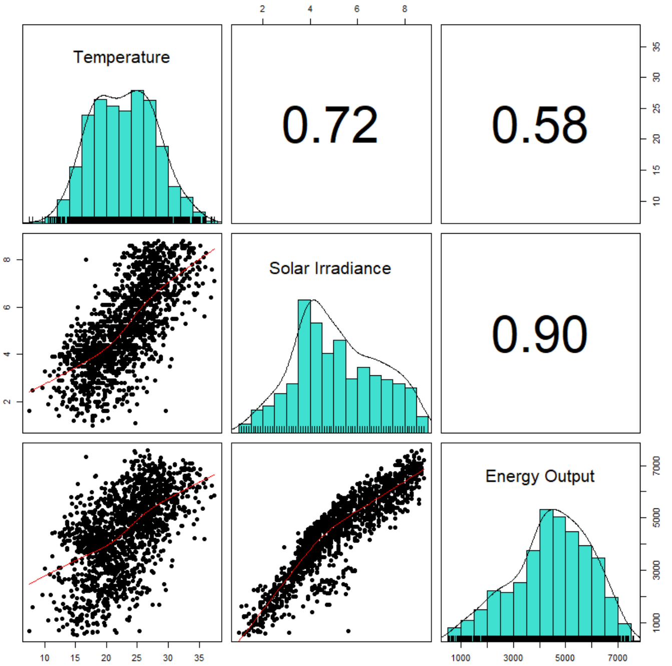

Figure 4.3: Pairs plot of the daily data of each measurement, histograms on the diagonal and Pearson correlations in the upper triangle.

To test for significance differences in energy output between temperature and month an analysis of variance was performed using the model

$$Energy = Month + Year + Month{:}Year + e$$

The analysis of variance for Energy Output in Table 4.1 shows a significant interaction between month and year. This means that Month and Year combinations affect energy output.

Table 4.1: AOV table for energy output by month and year

	Df	Sum of Sq	Mean Sq	F value	Pvalue
Month	11	1056866744	96078795	62.4601	<0.001
Year	4	49716108	12429027	8.0800	<0.001
Month: Year	40	330237648	8255941	5.3671	<0.001
Residual	1592	2448880951	1538242		

A multiple linear regression for energy output using Temperature and solar irradiance gives a relationship of

$$Energy = 1011.771 - 41.545\ Temperature + 852.350\ Solar\ Exposure$$

With an R-squared value of 0.8221.

This shows that the strong relationship between energy and weather can be modelled and there is a possibility that energy can be predicted from the weather.

Adding Monthly means into the equation makes Temperature non-significant.

$$Energy = -452.422 + 884.223\ Solar\ Exposure + Mean\ monthly\ Energy$$

This means that if we can predict the energy output for each month we can create a model using those averages and Solar Exposure.

4.2.1. Comparing the Car Park Data with Output from the Models

Figure 4.4 shows a positive linear relationship between the observed carpark data and the predicted energy output from equation 3.8, using daily temperature and irradiance values. Table 4.9 indicates that the predicted energy that incorporates a tilt angle for the solar panels has less percentage change for a tilt of 23°. The right-side figure in Figure 4.4 shows that the relationship between the tilted predictions is straighter but the fitted line is not centred. The fitted linear regression for the left figure has a coefficient of 1.18, the tilted predictions have a coefficient of 1.10.

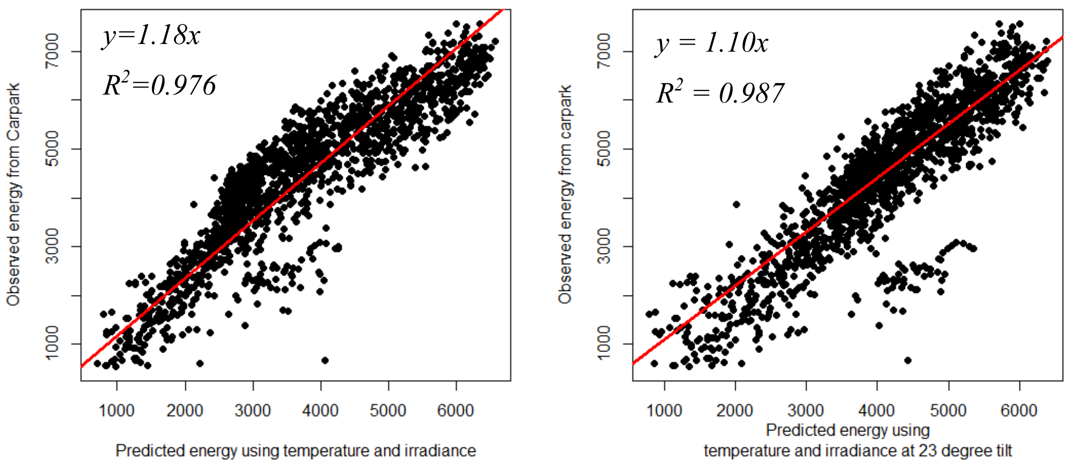

Figure 4.4: plot of daily carpark data versus the model that uses temperature and irradiance (equation 4.8). The figure on the left has no tilt and the figure on the right has a tilt of 23 degrees. The red line is a fitted line from a regression analysis.

Figure 4.4 also highlights that some of the observed values appear not to be in line with the rest. The plot of the raw data (Figure 4.1) shows that this corresponds to approximately early 2023. Without any prior knowledge of these points, it was assumed that the system failed to produce the correct energy at that time.

Figure 4.5 shows the energy predictions from all the methods. All methods follow the same pattern of higher energy production in summer than in winter. However, the largest variation in energy occurs in winter. The comparison baseline is given by the green line, and the observed carpark data is the turquoise line with the shading representing the confidence interval of the observed data. The wide confidence interval shows that the carpark data was highly variable. The predictions from HOMER and RETScreen lie close to the turquoise line, but SAM gives values much lower in winter than the other methods. The values mostly lie inside the confidence interval of the observed carpark data, with only SAM lying outside the area in the winter months. The calculated baseline values are always less than the carpark data, and the value for June is below the shaded area.

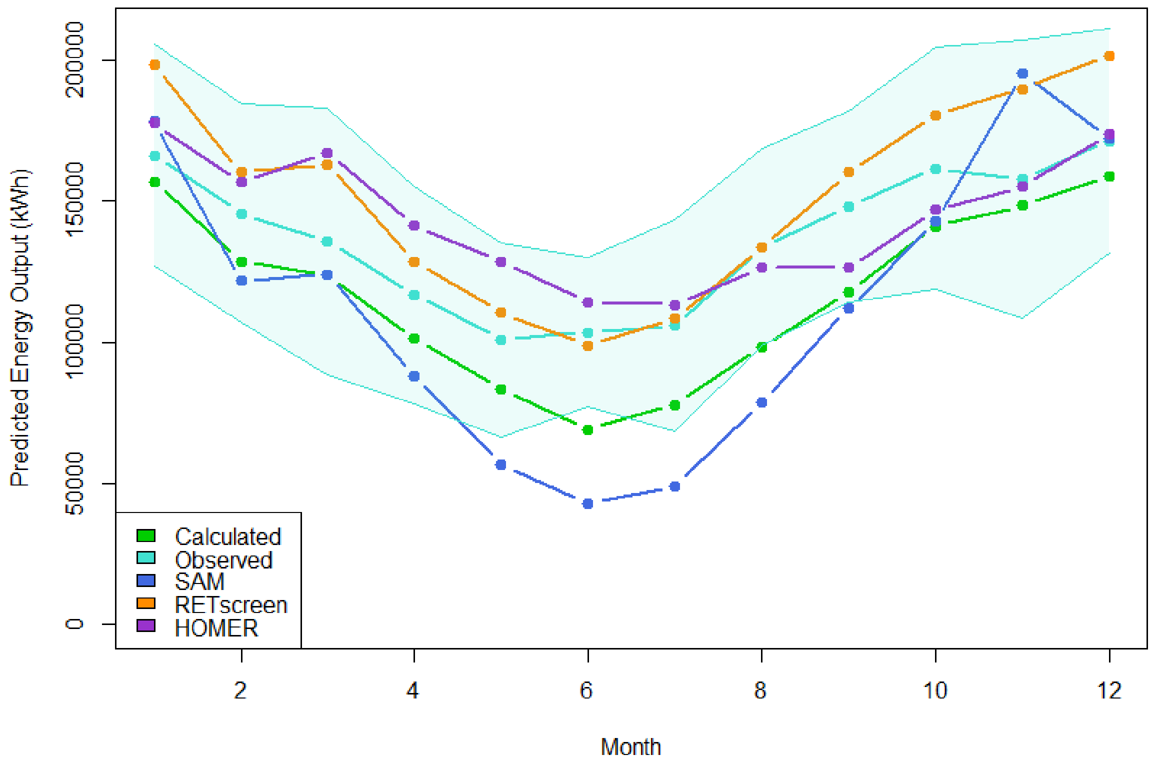

Figure 4.5: Comparison of the predicted energy output in one year using the long-term averages for temperature and solar irradiance. Shading represents the confidence interval of the observed carpark data.

Simple linear regression was computed using equation 3.12. This was used to compare each of the methods with the baseline values, the fitted lines are shown in Figure 4.6. All methods show a linear relationship with the manually calculated values; the values from SAM are the most deviated from 1, with a gradient of 1.63, and RETScreen is the closest to 1, with a gradient of 1.16.

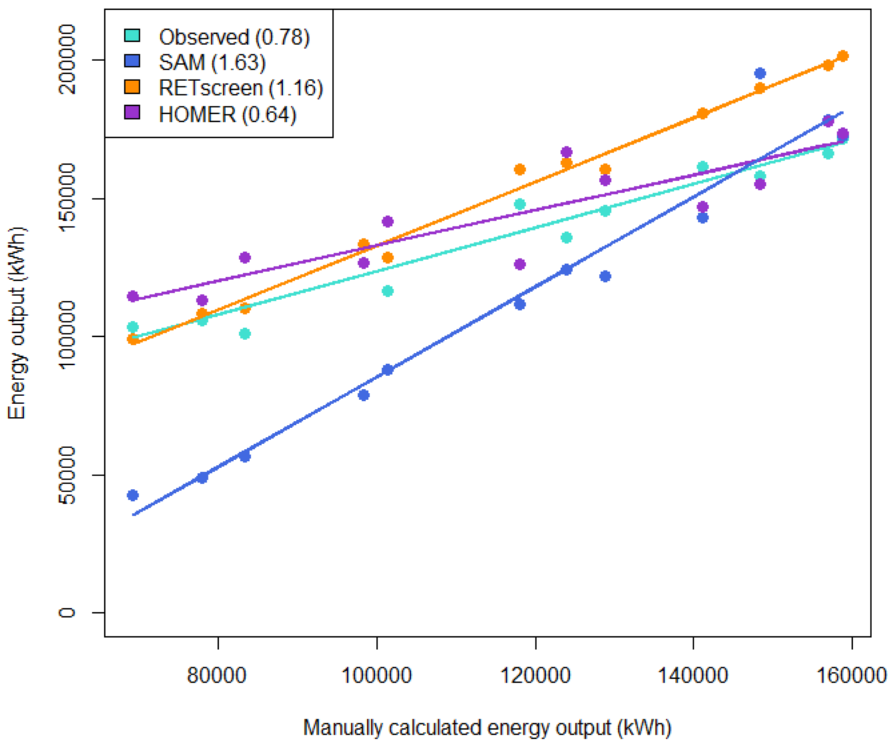

Figure 4.6: Linear regression of each prediction method and the observed carpark data against the manual calculations using system specifications. The numbers in brackets are the gradients of each fitted line.

4.3. Payback Comparisons

Table 4.2 presents a summary of all the methods used to calculate the payback period for the system as specified in Table 3.1, with the costs as specified by Table 3.2. The differences in initial costs are a result of the differing software methods. The baseline value is taken as the system specification as given by equations 3.1 to 3.3, where there was no inclusion of temperature, solar irradiance or cost inflation. The capacity factor gives the percentage of annual energy given by each method against the baseline value.

4.4. Methods Comparison

Table 4.2 gives the payback results along with the predicted annual energy and savings from all calculation methods. The estimated payback periods range from 16 years, the manual method that includes a percentage value for energy cost inflation. The longest payback period was 22 years, resulting from a manual calculation with only degradation. The capacity factor refers to the amount of predicted annual energy produced by the methods. There is a large range of different values from 73.2% up to 105% of the baseline value, which is the value calculated from the system specifications.

An assessment of each calculation method is given in Table 4.3. The baseline comparison method is the simple payback calculated value of 19 years using equation 4.3. Table 4.3 shows that each of the software gives values with percentage accuracies greater than 95%. Complexity and usability are qualitative factors based on user experiences. All the software had a component of learning requirement, which is subject to the prior knowledge of the user.

The inclusion of different parameters has a large effect on the payback period; Table 4.4 describes the effects. Parameters that cause the system to create less energy, such as degradation and shading, have the potential to increase the payback period. Weather parameters such as temperature and solar irradiance, and peripherals such as orientation and tilt, give a more accurate energy prediction, which leads to a more accurate payback period. Increased costs through maintenance will increase the payback period, which is also affected by the cost of the energy.

Table 4.2: Payback results given by all analysis methods alongside the predicted or calculated annual energy output, annual savings, and initial costs. The capacity factor refers to the percentage of the annual energy output from the system specifications and the annual energy output from each method (equation 3.11).

Method	**Results**				
	Payback	**Annual energy output (kWh/year)**	**Annual savings/revenue ($/year)**	**Initial Cost ($)**	**Capacity Factor (%)**
Software					
HOMER	19 years	1,840,000	279,000	5,970,000.00	105
SAM	20 years	1,300,000	192,000	4,000,000.00	75
RETScreen	19.3 years	1,720,000	144,000	3,820,000.00	98
PC3D	NA	NA	NA	NA	NA
Manual Methods					
System specifications	19 years	1,750,000	201,000	3,825,935.20	100
Data	20.8 years	1,602,386	184,274.	3,825,935.20	91.6
Degradation	22 years	Decreases per year from 1,750,221 to 1,422,382	Decreases from 198020 to 163573	3,825,935.20	90.1
Degradation + Cost inflation	16 years	Decreases per year from 1,750,221 to 1,517,148	Increases from 198020 to 307371	3,825,935.20	90.8
Predicted long term weather data + degradation + cost inflation	19 years	Decreases per year from 1,406,17 to 1,189,894	Increases from 16170 to 275314	3,825,935.20	73.2

Table 4.3: Comparisons between different methods, complexity refers to the level of prior knowledge that a user needs, usability is how straightforward the method is to run and retrieve, and requirements are a list of data and/or computer requirements.

Method	**Results**			
	Accuracy	**Complexity**	**Usability**	**Requirements**
HOMER	99%	Some of the information is not easy to understand without guidance, but there is comprehensive help available online. The capital amount of the system is not the same as the value that was put in.	The menus are good. There is a very schematic diagram that shows the components that have been included in the model. User experience is – provide a rating on a scale The Jinko Solar module information was automatically filled in.	Knowledge of the system specifications and load requirements. Output is in USD, so inflation and electricity prices need to be input manually.
SAM	95%	Requires some investigations before inputting financial values. Was difficult given the scarce amount of data we were given.	The menus are easy to follow. The Jinko Solar module information was automatically filled in.	Needs costs need to be in terms of kWdc/units so values need to be transformed.
RETScreen	98%	Allows inputs for every type of fuel and every type of end use. Gives more outputs than are needed. Can input electricity use.	The menus are easy to follow. Requires prior knowledge of end use. The Jinko Solar module information was automatically filled in.	System Specifications and individual component costs and loads.
PC3D	NA	Quite difficult to use, no fill in boxes to guide you through the process. No database lookups for modules	There are no financial aspects	Module specifications as presented in Table 3.1.
Manual	NA	Depending on which parameters are used the complexity can vary, requires a variety of mathematical techniques and can be time consuming if all possible variables are to be addressed	Manual Methods vary between simple and complex mathematical equations that depend on the user’s comprehension of these processes.	Requires information on weather data, PV specifications and financial data such as various costs of energy and materials. Also, a calculator, Excel or similar tool.

Table 4.4: List comparison of different assumptions and their effects on calculating the payback period.

Assumption	Results			
	Effects on Results	**Ease of Incorporating**	**Data Required**	**Notes**
Temperature and solar irradiance	Decrease in payback, more accurate	Requires a moderately complex equation and data	Daily data from BOM, easy to find and download	Not possible to predict future temperatures, so we need to use long-term monthly averages
Degradation	Increase in payback	Requires a simple equation	Degradation facts from the manufacturer's specifications	Can be assumed from the decrease in annual energy outputs.
Energy cost	Large decrease in payback when accounting for inflation	Requires a simple equation	Purchase cost, sell-back costs and estimated annual inflation	Can be difficult to find due to different electricity companies and variations in price for government versus residential
Panel Orientation and Tilt	Change in irradiance resulting in more accurate energy predictions	Requires a moderately complex equation and measurements to be taken	Latitude	Simple calculation using latitude and trigonometry
Shading and Soiling	Shade would lower the energy output. High soil/ground temperature would decrease panel efficiency.	Requires complex equations, measurements taken from the area and data	Cloud cover can be obtained from BOM. No information available on shade. Ground/soil temperature can be measured	Shade caused by trees would be easy to calculate. Soil/ground temperature can be measured if planned in advance.
Maintenance Costs	Will reduce the amount of savings and increase in payback time	Requires a simple equation and can be included in the basic payback formula	Need to know how much was spent on maintenance each year.	Might be difficult to predict and build a model that allows it to change each year.

4.4.1. HOMER

HOMER can simulate thousands of different systems and connects to the internet to download the system of interest, which in this case is the Jinko mono-crystalline PERC. It can input weather data, although it must be in a specific format and only for a single year. The specifications used do not mention a converter or battery, but they reference a Sunny-power inverter, indicating that a converter and battery will need to be selected. HOMER provides a comprehensive report for a range of input values and can calculate payback. The average monthly use from the data is input as the monthly load, and it is possible to simulate a range of power outputs using the specifications. With a limited amount of information about the solar car park system, certain elements, such as battery storage, must be selected without the required information. However, if these values remain constant across all simulations, it is still feasible to compare a range of inputs.

4.4.2. SAM

SAM finds its own weather using a file system that doesn't appear to be able to be put in as a csv file, although it was quite easy to put in the latitude and longitude and find the correct location. Comparing this data with that from the Bureau of Meteorology (BOM), they appear to be accurate. When first opening SAM, it's required to know which section to start in, for solar car park, Photovoltaic > single owner was selected, but there were many other options. It was quite simple to find the required modules Jinko 285, put in the user-defined section to change the parameters and number of solar cells. This part of the process was user-friendly and didn't require prior experience with the program.

The Inverter was easy to select, but none of the parameters could be changed, so SAM relied on data from each manufacturer, assuming no modifications had been made. The inverter was SMA America: STPS60US-20, which is the equivalent to the Sunny Tripower 60. There are a lot of comprehensive options for inflation, depreciation, etc. and the user can choose to either use the defaults or input their own. The cost of the system doesn't seem to be able to be input by the user, instead SAM calculates it from the specified modules. This is the price today not the price in 2017 when our panels were installed.

4.4.3. RETScreen

Has the capacity to itemise all the facilities and appliances connected to the PV system and their respective electricity use. A single value that represents how much we use from the spreadsheet data was selected for solar car park. The demo version of the software doesn't allow the project to be saved. It would be good for someone wanting to put up a new solar on their roof, but for a larger commercial complex, bulk values would be better than itemising everything. The components, Jinko Solar panels etc. were easy to find. The summary of the data based on the size of the panels and the weather from BOM was of good quality.

4.4.4. PC3D

PC3D is an open-source numerical analysis program for simulating the internal operation of silicon solar cells. It uses Excel to provide a familiar, easy-to-use interface for specifying parameters and exploring the solution space. It is ideal for those seeking to obtain a better understanding of solar cell physics but having limited time to learn a new program. Easy to download and install if the user owns Excel. Simulates how the solar cell works using multiple parameters. It is easy to see instructions on each cell that define what each cell is. Doesn't calculate any financial information, no payback. Specifications need to be put in manually with no capacity for looking up the Jinko specifications. Data is not available for recombination or illumination, so those uses could not be tested.

4.4.5. Manual Methods

4.5.5.1 Expected Payback Using System Specifications

The manufacturer's specifications (Table 3.1) can be used to find the expected energy output and then the expected payback using equations 3.1 to 3.3.

PV capacity = 1090kW, hours/year = 8760 and capacity factor = 0.1833

$$Annual\ energy\ generated = PV\ capacity\ \times capacity\ factor \times hours\ per\ year$$

$$= 1090 \times 0.1833 \times 8760$$

$$\approx 1750000\ kWh/year \tag{4.1}$$

Electricity savings as 6c-7c, on average this is \$0.065

LGC revenue is between \$45 and \$55 per MWh, this converts to \$0.05 per kWh

Therefore, the total value per kWh is \$0.065 + \$0.05 = \$0.115

$$Annual\ Savings = Annual\ Energy\ Output \times Total\ Value\ per\ kWh$$

$$= 1750000\ \times 0.115$$

$$\approx \$201000 \tag{4.2}$$

The payback period can now be calculated as

$$Payback\ Period\ = \frac{Total\ System\ Cost}{Annual\ Savings\ from\ Solar}$$

$$= \frac{3825935.20}{201000} \approx 19\ years \tag{4.3}$$

Using the specifications from the Jinko manufacturer, the payback period would be approximately 19 years (Table 4.2).

4.5.5.2 Expected Payback from Data

Using the observed car park data, the average annual energy output was 1,602,386 ± 86721 kWh/year

$$Payback\ Period\ = \frac{3825935.20}{1602386 \times 0.115} \approx 20.8\ \pm 1.2\ years \qquad (4.4)$$

The average energy output recorded is 147,000 kWh lower than the expected value from the system specifications, increasing the payback period by approximately 1.8 years (a change of 9.5%) (Table 4.2).

4.5.5.3 System Degradation

Degradation $D = 3\%$ in year 1, linear 0.8% per year after that (Table 4.1). Energy predicted using degradation can be found using equation 3.4, with year 1 = 2020, and using the values given in the carpark data the total Energy in 2020 was 1712478 kWh.

$$E_t = E_1\left[1 - \frac{D}{100}(t-1)\right] \qquad (4.5)$$

The unbalanced data does not have 365 observations per year. Data can be adjusted using the following

Energy = $1712478\frac{365}{363} = 1721913\ kWh$ per 365-day year. This value is E_1 in equation 4.5.

For $t=2$ (year 2, 2021) the energy can be predicted from the output from year 1. This formula assumes that degradation was the only factor that caused a change in energy output.

$$E_2 = 1721913[1 - 0.03] = 1670255\ kWh \text{ per 365-day year.}$$

From the carpark data, the total annual energy for 2021 = 1662643 kWh, which is 0.46% lower than the predicted degradation value.

After the first year the degradation slows to 0.8%, so the predicted energy output for $t=3$ (2022) is

$$E_3 = E_2[1 - 0.008] = 1670255[1 - 0.008] = 1656893\ kWh.$$

Table 4.5 shows the resultant value of following this process starting at the 2020 carpark total energy value and adjusting each yearly total for 365 days. Figure 4.7 shows that the observed annual energy from the carpark data decreases much faster than the expected degradation from the specifications. Note that the data for 2024 is only up to August and therefore may not represent the full year.

Table 4.5: Observed total annual energy output converted to a 365-day year, energy of the predictive model based on the degradation with 2020 as the initial yearly total and the percentage of error (equation 3.11).

t	Year	Number of days	Total Energy Output	Output per 365 days	D	Energy with degradation	% Error
1	2020	363	1712478	1721913	0	1721913	
2	2021	361	1644423	1662643	0.03	1670255	0.46
3	2022	329	1427185	1583351	0.008	1656893	4.44
4	2023	332	1441558	1584845	0.008	1643638	3.58
5	2024	242	1001695	1510821	0.008	1630489	7.34

Figure 4.7: Observed total annual energy from the car park data and the predicted degradation of the data using equation (4.5) starting from the 2020 total.

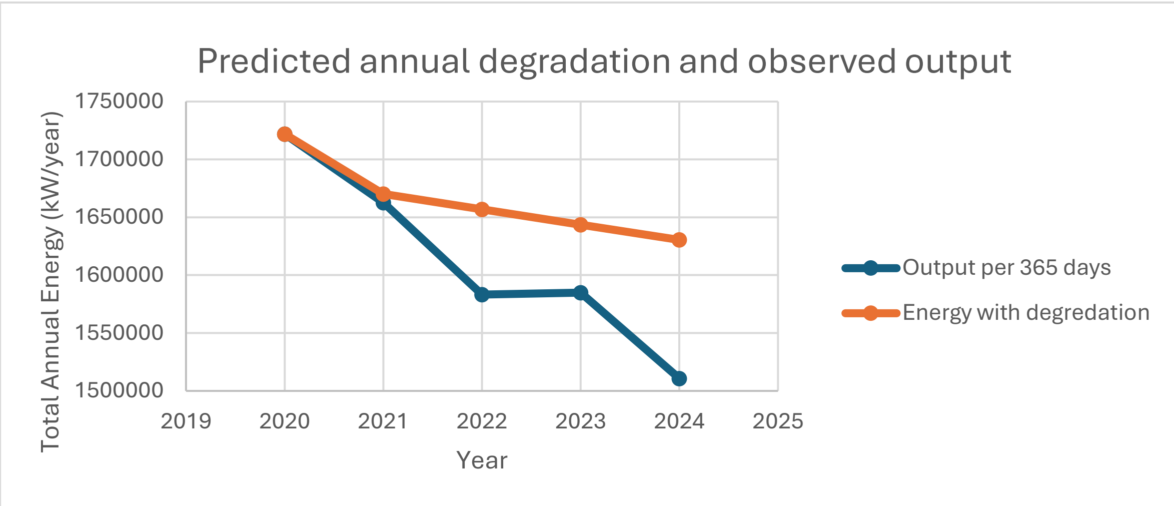

Table 4.6: To calculate the payback period use equation (4.2) to find the energy cost for each predicted annual energy assuming no change in cost per kWh.

t	D	Energy	Cost	Cumulative sum
1	0	1750221	201275.50	201275.50
2	0.03	1697715	195237.23	396512.73
3	0.008	1684133	193675.34	590188.07
4	0.008	1670660	192125.93	782314.00
5	0.008	1657295	190588.92	972902.92
6	0.008	1644036	189064.21	1161967.14
7	0.008	1630884	187551.70	1349518.84
8	0.008	1617837	186051.29	1535570.12
9	0.008	1604894	184562.88	1720133.00
10	0.008	1592055	183086.37	1903219.37
11	0.008	1579318	181621.68	2084841.05
12	0.008	1566684	180168.71	2265009.76
13	0.008	1554150	178727.36	2443737.12
14	0.008	1541717	177297.54	2621034.66
15	0.008	1529384	175879.16	2796913.82
16	0.008	1517148	174472.13	2971385.95
17	0.008	1505011	173076.35	3144462.30
18	0.008	1492971	171691.74	3316154.03
19	0.008	1481027	170318.20	3486472.24
20	0.008	1469179	168955.66	3655427.90
21	0.008	1457426	167604.01	3823031.91
22	0.008	1445766	166263.18	3989295.09

The payback period is when the cumulative sum of the energy value first exceeds the initial cost of \$3,825,935.20 (equation 3.7), from Table 4.6, this is 22 years (Table 4.2). This means that when assuming no change in energy costs and allowing for system degradation the energy output will decrease over time extending the payback period.

Table 4.7: Payback calculations using degradation and the initial year as data from 2020.

t	D	Energy	Cost	Cumulative Sum
1	0	1721913	198020.01	198020.01
2	0.03	1670255	192079.41	390099.42
3	0.008	1656893	190542.78	580642.20
4	0.008	1643638	189018.43	769660.63
5	0.008	1630489	187506.29	957166.92
6	0.008	1617445	186006.24	1143173.15
7	0.008	1604505	184518.19	1327691.34
8	0.008	1591669	183042.04	1510733.38
9	0.008	1578936	181577.70	1692311.08
10	0.008	1566305	180125.08	1872436.16
11	0.008	1553774	178684.08	2051120.25
12	0.008	1541344	177254.61	2228374.85
13	0.008	1529013	175836.57	2404211.43
14	0.008	1516781	174429.88	2578641.31
15	0.008	1504647	173034.44	2751675.75
16	0.008	1492610	171650.16	2923325.91
17	0.008	1480669	170276.96	3093602.88
18	0.008	1468823	168914.75	3262517.62
19	0.008	1457073	167563.43	3430081.05
20	0.008	1445416	166222.92	3596303.98
21	0.008	1433853	164893.14	3761197.11
22	0.008	1422382	163573.99	3924771.11

When using the observed carpark data, the payback period is still 22 years. The difference between the predicted data in Table 6 and the observed data in Table 4.7 is after 22 years the cost of the data is $64,523.89 more than the cost of the prediction.

4.5.5.4 Electricity Price Increase

The estimated electricity price increase for Queensland is approximately 5% per annum (Ergon). The system is degrading while simultaneously increasing in value due to rising electricity costs.

R = 5%/year

In year 1 $C = 0.115$ (total value per kWh) and using equation 3.5:

$$C_t = \left[C_1\left(1 + \frac{R}{100}\right)^{t-1}\right]E_t$$

For year 4 (2023), $t=4$ and $E_t = 1547676$

$$C_4 = [0.115(1 + 0.05)^3] \times 1547676 = \$206037.30 \qquad (4.6)$$

The value of energy can be calculated using equation 3.6:

$$V_t = \frac{C_t}{\left[\left(1+\frac{1}{100}\right)^{t-1}\right]} = \frac{206037.30}{\left(1+\frac{1}{100}\right)^2} = \$199977.70 \qquad (4.7)$$

Table 4.8: Predicted energy output and cost projected using the calculations from equation (4.2) as the initial total annual energy

t	D	Energy with degradation	Energy cost	Energy value	Cumulative sum
1	0	1750221	201275.50	201275.50	201275.50
2	0.03	1697715	204999.09	202969.40	404244.90
3	0.008	1684133	213527.06	209319.73	613564.63
4	0.008	1670660	222409.78	215868.74	829433.37
5	0.008	1657295	231662.03	222622.66	1052056.03
6	0.008	1644036	241299.17	229587.88	1281643.91
7	0.008	1630884	251337.22	236771.03	1518414.94
8	0.008	1617837	261792.84	244178.91	1762593.85
9	0.008	1604894	272683.43	251818.57	2014412.42
10	0.008	1592055	284027.06	259697.25	2274109.66
11	0.008	1579318	295842.58	267822.43	2541932.09
12	0.008	1566684	308149.63	276201.82	2818133.92
13	0.008	1554150	320968.66	284843.39	3102977.31
14	0.008	1541717	334320.95	293755.32	3396732.62
15	0.008	1529384	348228.71	302946.08	3699678.70
16	0.008	1517148	362715.02	312424.39	4012103.09

The payback period, when the cumulative sum of the energy value first exceeds the initial cost of $3,825,935.20, is less than 16 years. By adding the increasing cost of the energy on top of the system degradation, the payback period has decreased from 22 to 16 years (a decrease of 27%) (Table 4.2).

Table 4.9: Predicted energy output using carpark for the initial year with degradation and allowing for cost inflation.

t	D	Energy with degradation	Energy cost	Energy value	Cumulative sum
1	0	1721913	198020.01	198020.01	198020.01
2	0.03	1670255	201683.38	199686.52	397706.52
3	0.008	1656893	210073.41	205934.13	603640.66
4	0.008	1643638	218812.46	212377.22	816017.88
5	0.008	1630489	227915.06	219021.90	1035039.77
6	0.008	1617445	237396.32	225874.46	1260914.24
7	0.008	1604505	247272.01	232941.42	1493855.66
8	0.008	1591669	257558.53	240229.49	1734085.15
9	0.008	1578936	268272.96	247745.58	1981830.74
10	0.008	1566305	279433.12	255496.83	2237327.57
11	0.008	1553774	291057.54	263490.59	2500818.16
12	0.008	1541344	303165.53	271734.46	2772552.62
13	0.008	1529013	315777.22	280236.25	3052788.87
14	0.008	1516781	328913.55	289004.04	3341792.91
15	0.008	1504647	342596.35	298046.14	3639839.05
16	0.008	1492610	356848.36	307371.15	3947210.20

The payback period when using observed data is closer to 16 years than the prediction in table 4.8. The difference in cost is \$64,892.88 less for the observed data and \$368.99 more then degradation without energy price increase

4.5.5.5 Temperature and Solar Irradiance

To include temperature and solar irradiance into the prediction of energy calculation, use equation 3.8 with

P = photovoltaic array at peak power = 1090 kWp
f = derating factor = 3% (year 1)
G_T = solar irradiance striking the PV array = 5.31 kWh/m^2 (for Toowoomba on average across the 4 years)
$G_{(T,STC)}$ = solar irradiance under standard test conditions = 1 kW/m^2
K_p = temperature coefficient = -0.39%/degC
T_c = photovoltaic temperature = 45 degC
T_{STC} = ambient temperature = 25 degC

$$PV_{poweroutput} = P_{\{pv,STC\}} f_{PV} \frac{G_T}{G_{\{T,STC\}}} [1 + K_P(T_c - T_{STC})]$$

$$= 1090 \times 0.008 \times 5.31 \times \left(1 - 0.0039(45 - 25)\right)$$

$$\approx 160.09kWp \tag{4.8}$$

Power output is proportional to solar irradiance, temperature coefficient and change in temperature. Both factors change monthly. Figure 4.8 shows a graph of the predicted power output per month using the observed BOM temperatures and solar irradiances from 2020.

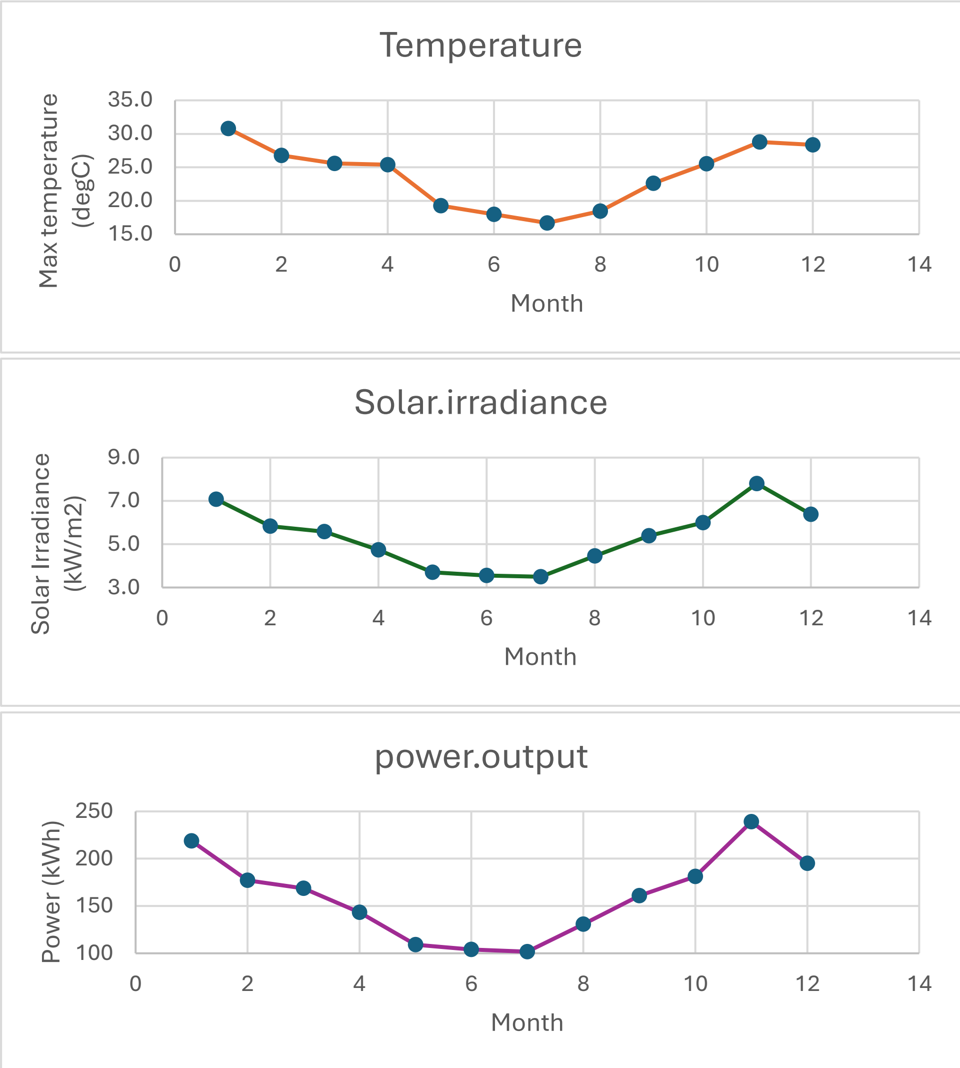

Figure 4.8: Power output (bottom) calculated by equation (4.8) using the observed temperatures and solar irradiances from 2020 carpark data (top and middle).

Since the temperature and solar irradiance can't be predicted for dates in the future, long-term averages were used along with equation 4.8 to predict the energy. These were compared to the across-year averages from the carpark data as presented in Table 4.10. The observed temperatures and solar irradiance values were all within 10% of their respective long-term averages. The observed energy output values were all higher than those predicted using equation 4.8 with the winter months showing the largest percentage changes from the predicted values. The observed 5-year irradiances are mostly lower than the long-term average, but they are all less than 7% different. However, the observed energy output is up to 50% higher than the predicted values, especially in the winter months, with June's output being 50% higher than predicted. The total energy across the average year was 17% larger than the predicted value. Table 4.11 shows the payback period using the total annual energy predicted from the average long-term temperatures and irradiances from Table 4.10, along with degradation and cost inflation. Using these values, the payback period is between 18 and 19 years.

Table 4.10: Long-term monthly temperatures and solar irradiance. Energy calculated from equation 4.8. Averages from the 5 years of carpark data and percentage change (equation 3.11) for all observed values.

Month	Maximum Temperature (°C)	Average Irradiance (kW/m^2)	Month total calculate (kWh)	Observed Temperaure (°C)	%Δ	Observed Irradiance (kW/m^2)	%Δ	Month Total Observed (kWh)	%Δ
Jan	28.4	6.9	157000	28.3	-0.4	6.7	-3.0	166343	6
Feb	27.6	6.2	128810	27.6	0.0	6.2	-0.1	145753	13
Mar	26.1	5.5	123945	25.5	-2.4	5.2	-6.2	135681	9
Apr	23.2	4.7	101248	22.9	-1.1	4.6	-2.5	116741	15
May	19.8	3.8	83363	19.2	-3.1	3.7	-2.6	100898	21
Jun	17.0	3.3	69210	17.2	1.5	3.5	6.1	103605	50
Jul	16.7	3.6	77917	16.3	-2.2	3.5	-1.7	105892	36
Aug	18.9	4.5	98335	19.7	4.0	4.5	-1.0	133533	36
Sep	22.3	5.5	118028	21.8	-2.2	5.4	-2.5	148095	25
Oct	24.6	6.3	141077	24.7	0.2	6.2	-2.4	161677	15
Nov	26.3	6.8	148423	25.9	-1.5	6.5	-4.2	157995	6
Dec	27.7	7.0	158811	27.7	0.0	7.1	1.2	171472	8
Annual Total			1406172					1647688	17

Table 4.11: Payback table using the predicted total annual energy from Table 4.10, degradation and cost inflation.

t	D	Energy with degradation	Energy cost	Energy value	Cumulative sum
1	0	1406172	161709.79	161709.79	161709.79
2	0.03	1363986	164701.42	163070.71	324780.50
3	0.008	1353075	171553.00	168172.73	492953.23
4	0.008	1342250	178689.60	173434.37	666387.60
5	0.008	1331512	186123.09	178860.63	845248.23
6	0.008	1320860	193865.81	184456.67	1029704.90
7	0.008	1310293	201930.63	190227.79	1219932.69
8	0.008	1299811	210330.94	196179.47	1416112.16
9	0.008	1289412	219080.71	202317.36	1618429.52
10	0.008	1279097	228194.47	208647.29	1827076.81
11	0.008	1268864	237687.36	215175.27	2042252.08
12	0.008	1258713	247575.15	221907.48	2264159.56
13	0.008	1248643	257874.28	228850.33	2493009.89
14	0.008	1238654	268601.85	236010.40	2729020.29
15	0.008	1228745	279775.69	243394.49	2972414.78
16	0.008	1218915	291414.36	251009.60	3223424.38
17	0.008	1209164	303537.19	258862.97	3482287.35
18	0.008	1199490	316164.34	266962.05	3749249.40
19	0.008	1189894	329316.78	275314.53	4024563.93

4.5.5.6 Adjusting for Panel Peripherals

The latitude of the carpark is approximately 27.56°S, the declination can be calculated using equation 3.10. Figure 4.9 shows the change in irradiance for panel tilt angles of 0, 10, 30, 45, 60 and the optimum angle of 23.43 degrees. Larger tilt angles increase solar irradiance value in winter and less in summer. Table 4.12 shows that on day 30 (30th January), the solar irradiance decreases when the angle increases, but for day 210 (29th July) the solar irradiance increases when the tilt angle increases.

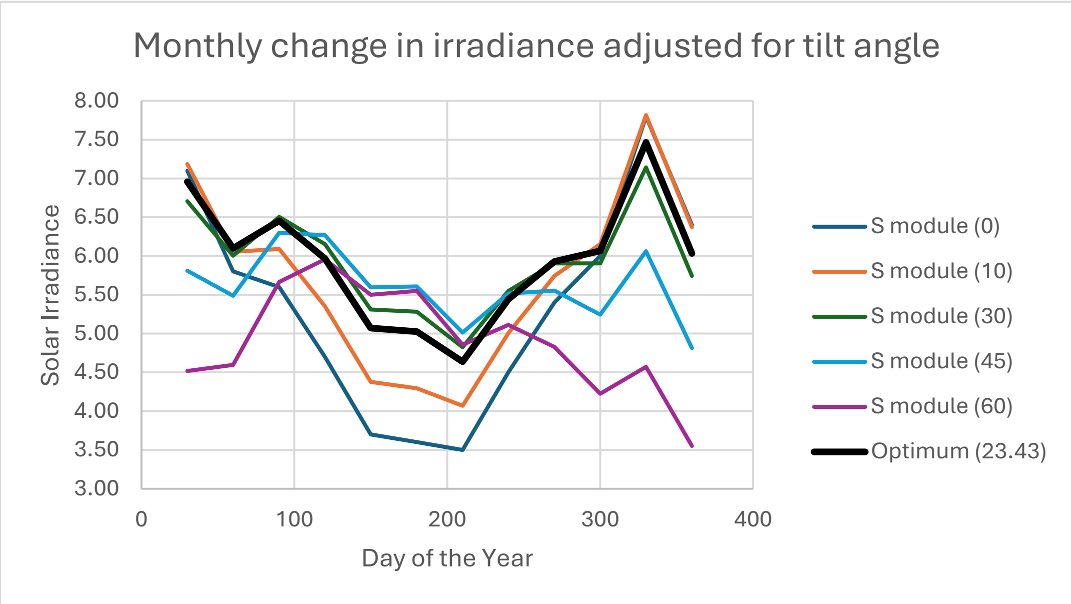

Figure 4.9: Solar irradiance adjusted for tilt angle, the value in brackets indicates tilt angle (β).

Table 4.12: Calculations of solar irradiance using equation (3.9) for 30 days apart

day	**Declination (10)**	**α**	**S module (β=0°)**	**S module (β=10°)**	**S module (β=30°)**	**S module (β=45°)**	**S module (β=60°)**	**Optimum (β=23.43°)**
30	-18.07	81.07	7.10	7.19	6.71	5.81	4.52	6.96
60	-8.33	71.33	5.80	6.05	6.00	5.49	4.60	6.10
90	3.57	59.43	5.60	6.09	6.50	6.30	5.67	6.45
120	14.55	48.45	4.70	5.35	6.15	6.27	5.96	5.97
150	21.73	41.27	3.70	4.38	5.31	5.60	5.50	5.07
180	23.25	39.75	3.60	4.30	5.28	5.61	5.55	5.02
210	18.71	44.29	3.50	4.07	4.82	5.01	4.86	4.64
240	9.29	53.71	4.50	5.01	5.55	5.52	5.11	5.44
270	-2.55	65.55	5.40	5.74	5.90	5.55	4.83	5.93
300	-13.73	76.73	6.00	6.15	5.90	5.24	4.23	6.07
330	-21.32	84.32	7.80	7.82	7.14	6.06	4.57	7.47
360	-23.36	86.36	6.40	6.37	5.75	4.81	3.55	6.03

Table 4.13: Total annual energy output in kWh from the carpark data. Predicted total annual energy output using daily temperature and solar irradiance. Predicted energy output using solar irradiance that had been adjusted for tilt angle. Percentage erros were calculated using equation 3.11.

Year	Solar Carpark	Predicted (no tilt)	%Δ	Predicted (23° tilt)	%Δ	Predicted (45° tilt)	%Δ	Predicted (60° tilt)	%Δ
2020	1721913	1406010	-18	1547856	-10	1452606	-16	1264436	-27
2021	1662643	1349996	-19	1490265	-10	1401980	-16	1222935	-26
2022	1583351	1300392	-18	1454879	-8	1384916	-13	1220192	-23
2023	1584846	1430073	-10	1570037	-1	1469802	-7	1276689	-19
2024	1510821	1235550	-18	1476653	-2	1483588	-2	1364773	-10

Table 4.13 shows that the predicted annual energy using equation 4.8 with observed temperature and solar irradiance is between -19 % and -10 % less than the observed values. When adjusting the solar irradiance using equation 3.9, the error for a tilt angle of 23° decreases to between -1% and -10%. The 23° tilt predictions are a better model for the carpark data.

To predict the payback period when using predictions based on temperature and irradiance we will assume average monthly values for all years.

4.5.5.7 Temperature Compensation Calculations

The temperature effect on voltage and power from PV panels is linear and increases as temperature increases. If the difference between the standard test conditions and the operating temperature is low, the energy output will decrease (see equation 4.8). Using the temperature coefficients as given by the Jinko specifications, we can see how the voltage and power are affected. Using the system specifications, the maximum voltage would decrease from 32V to 29.67V and the Voc (maximum voltage with no load connected) would decrease from 38.7V to 36.46V (equation 4.9). Similarly for power, under normal conditions the power of 270W would decrease to 248.94W (equation 4.10).

For the Jinko panels *Voc = 38.7V* and temperature coefficient of *Voc = -0.29%/*°C

$$38.7 \text{ x } (-0.0029) = -0.112 \text{ V/°C}$$

Using the nominal cell operating temperature of 45°C, at 25° the temperature difference is multiplied by -0.112; 45°-25°=20° x -0.112 = -2.25V

This means that the maximum voltage power (*Vmp*) of 32.0V would reduce to

$$32 - 2.25 = 29.7\text{V, and the Voc of 38.7V would reduce to } 38.7 - 2.25 = 36.4\text{V.} \quad (4.9)$$

Jinko gives a maximum power of 270W and the temperature coefficient of *Pmax = -0.39%/*°C

$$270 \text{ x } (-0.0039) = -1.053$$

At a cell temperature of 45°C

$$(45-25) \text{ x } (-1.053) = -21.06\text{W}, 270\text{W}-21.06\text{W} = 249\text{W} \quad (4.10)$$

CHAPTER 5: DISCUSSIONS AND CONCLUSION

5.1. Summary

It is important to examine the current methods used in various scientific fields due to the progressing technology involved. For the payback period in the renewable energy field, the most common methods are either to use software (the most common being HOMER) or to use a simple manual method. Some methods use a variety of data and parameters to find accurate payback periods, while others use the most basic. While these changes affect accuracy, they can also affect ease of use. The following discussion will focus on the software, its accuracy, ease of use and quality of data. Additionally, discussions will be presented on the manual methods, including an analysis of the most impactful factors and the complexity of including these parameters.

5.2. User Review of the Software

The software tested for calculating payback period includes HOMER, SAM, RETScreen and PC3D. While the first three are examples of common software, the latter is a less common software used to test the viability of using macros-based software. This will also answer the question of how manual methods compare to software-based tools in terms of accuracy, accessibility, and versatility.

5.2.1. HOMER

The HOMER software system is a common tool for energy simulation due to its ability to simulate different systems. It enables users to search the internet to download location and system specifications, thus prefilling the parameters. It can input weather data, however, it only allows one year, which is a limitation when wanting to simulate multiple years of energy output for the payback period. Using long-term averages is only accurate in average years, although future weather cannot be predicted, it would be advantageous to predict the power output over a range of different weather options. Another good facility is the capacity to upload user-defined power loads, which allows users to research multiple scenarios. In this study we used mean monthly power outputs as the required load input. This has resulted in realistic outputs.

For new users, it was not straightforward to use, it requires knowledge to interpret the required inputs. The data used for this study was missing a lot of information needed for HOMER to operate appropriately, such as battery storage and inverters, which made it difficult to simulate systems that could be compared to the provided data. This adds some inaccuracies to the simulation. The HOMER instruction manual states that these components are necessary, which causes doubt about the output.

Based on US dollars, users from outside the USA need to be careful to change the financial aspects accordingly, especially if the payback period is the desired outcome, since HOMER uses databases to gather the electricity prices. However, it does present the user with the possibility to input their own financial data.

HOMER has a methodology for calculating payback periods, based on the performance of other solar systems in the area. The list of output scenarios was not extensive for the specific system considered in this study. It would be an excellent software choice for manufacturing companies that are simulating data to provide a report to customers who are seeking to buy solar panels. The companies have all required information for their calculations and are open to multiple outputs rather than trying to compare the results to a known system.

The main advantage of HOMER is for hybrid systems that include both solar panels and battery storage. Since the data in this study does not include battery storage, HOMER was not used to its full capacity. While HOMER is a powerful tool for solar simulation, there are areas that cast doubt on its accuracy due to the lack of knowledge that is held in its proprietary nature. This means the uncertainty of the calculation is still not as well-known as expected. HOMER provided a payback period of 19 years, equal to the expected value (Table 4.2).

5.2.2. SAM

Like HOMER, SAM features a menu system that enables users to search for their location and system specifications. This simplifies the process of retrieving weather and system information. SAM doesn't allow users to input a CSV file, which is a downside when you need to predict energy output using user-defined weather data. You can put in a latitude and longitude, and it will collect the data from BOM, which is accurate. Users also need some understanding of the system when entering the specifications. There are numerous options available when first starting the software, which can be confusing if you want a simple simulation of a known system. A company wanting to provide multiple scenarios to a potential client would benefit from this flexibility. Finding the Jinko 285 was straightforward, and the capacity to modify the number of panels was a nice feature of SAM.

The lack of information associated with inverters and how they are used with the software caused some issues in not understanding what the impact the lack of an inverter does to the calculated outputs. A similar inverter was put into the program, but it is unknown how much this affected the simulation. SAM's output includes spreadsheets detailing simulated energy output and annual financial specifications. While the payback period is not explicitly stated, users can track the balance and note when it reaches zero, allowing them to draw conclusions about the payback period. Looking at the yearly output in a table enables a deeper understanding of the year-to-year values.

SAM gave a payback period of 20 years which was one year longer than the expected value (Table 4.2).

5.2.3. RETScreen

RETScreen has a very user-friendly interface with easy-to-follow options for inputting location and system specifications. The location option provides a map that can be used to fine tune the exact location without having to know the latitude and longitude as in the case of SAM. It contains very comprehensive electricity use options for all different types of electrical use in either a house or a workplace or factory. This would be a great resource for someone wanting to customise their purchase of solar panels.

As with HOMER and SAM it was simple to find the Jinko solar panels used in this study. RETScreen also has an extra input for the tilt angle, which can provide more accurate simulations. The final data comes as a large and comprehensive set of spreadsheets for financial and power outputs, either daily, monthly or yearly. One issue arose with the demo version; you cannot save the outputs to enable analyses and comparisons with the other methods. The resulting payback of 19.3 years was within 2% of the expected value of 19 years (Table 4.2).

For the scenario presented in this study, RETScreen was the most satisfactory software out of the 3 common ones, surpassing HOMER and SAM, during the investigations of these systems, all these factors were generally more satisfactory to use, manage and interpret from a personal level as well as a comparative viewpoint. All three software packages have many more extensive functions that were not explored here.

5.2.4. Other Software

Another software option is the open-source program PC3D. This runs as an Excel macro, so users of Excel would be familiar with its interface, removing the complication of learning a new type of software. Downloading and installing is easy. The cells within the program have pre-defined instructions available.

The downside is that there are no options for selecting a specific system such as the Jinko 285. Instead, you need to give the program all the specific details, which may be complicated for novice users. Calculating the payback period is not a feature of PC3D. However, it can be used to predict energy output from many different scenarios. The software had no facility to input financial data, electricity prices, or construction costs.

5.3. Parameter Analysis

When doing a manual calculation, it needs to be decided which parameters to account for and which data to use. To discuss the most optimal method of performing payback period analysis, it is necessary to discuss these individual assumptions, including the specifications of the PV itself, the weather and other exterior factors.

The real-life carpark data showed that the energy output had seasonal variability, high in summer and low in winter, the same variable pattern as both maximum daily temperatures and daily solar irradiance, proving that these are important parameters in computing energy output. A multiple linear regression model showed a significant interaction between month and year, indicating that the energy output varies per year, which is an indication of possible degradation of the system. The manually calculated daily energy showed strong agreement with the observed daily carpark values when incorporating an adjustment for panel angle. It was also evident that the observed data had a section of error where the system produced unrealistically low energy. This is an issue that needs to be addressed when using real-life data, but this research has shown that it is easy to detect these values and compensate for them.

When plotting the real-life energy output against predicted output from each of the software types, there were a lot of similarities, which gives confidence that the calculations for energy output are similar and the observed differences in payback period are due to other properties.

5.3.1. PV Specifications

The system specifications cover the information relating to the PV setup itself. Theoretically a user should have access to a selection of system types and will be able to choose, making access to this information quite easy. This includes the raw system specifications themselves, the information that can be used to estimate performance and financial parameters.

5.3.1.1 System Specifications

Based on the manual methods, the system size, number of panels and panel wattage all have the most effect on the predicted energy output. As seen in equations 3.1 to 3.3, the total energy output is proportional to the wattage; the larger the number of panels, the more energy is produced and, hence, more energy to sell back to the grid, resulting in a larger annual savings from the system.

The mounting system, or a fixed angle tilt, affects solar ratio, which is shown in equations 3.9 and 3.10. Panels that are flat will get the most solar irradiance in the summer months when the sun is more directly overhead. However, in winter, when the sun is lower, a panel that is tilted will have more solar exposure, resulting in a higher solar irradiance. Panel tilt is affected by latitude (equation 3.9). The amount of energy produced is indirectly proportional to the temperature (equation 3.8), so there needs to be a balance between the tilt angle and the solar collected. Summer will always tend to create more energy due to higher solar irradiance caused by the sun's closer proximity to the Earth. By tilting the panels more, a higher amount of energy can be collected during the colder months. The optimum tilt angle of panels in Southern Queensland is 23.43° (Negro 2022), at this angle the panels are exposed to a similar amount of solar all year round (Table 4.12). There is a need to combine this information with other sources since the payback calculation is based on total annual energy accumulation.

5.3.1.2 Performance Parameters

Degradation is evident in the recorded performance as the yearly energy produced does consistently decline across the five years of data (each year of the observed data has been adjusted to 365 days). The temperature coefficient, as seen in equation 5, affects PV power output by being multiplied by the output from the previous year and the degradation factor of 3% in the first year and 0.8% linearly thereafter. Figure 4.1 shows that the carpark data degrades faster than the predicted degradation when started with the same total annual output. This may be explained by the fact that the system was originally constructed in 2016, whereas the data starts in 2020, therefore a lot of the initial year degradation had already occurred before the data was observed. The degradation formula is heavily reliant on the previous year; if a year was not representative, the pattern of degradation would not be comparable to the predicted values. It is possible that 2020 may have been a non-representative year.

5.3.1.3 Financial Parameters

The total system cost as used throughout this study has been calculated on many different aspects (Table 2.2). The PV panels themselves only accounted for around 30% of the cost. Adding in components such as inverters and battery storage will add not just to the total cost but also to the ongoing maintenance. A lot of the cost was in labour and infrastructure relating to the car park itself. The information used in this study assumed no ongoing maintenance costs (as informed by the data provider). Any ongoing costs would add more complexity to the calculations. An ongoing percentage could be accounted for quite simply. However, a large expense such as having to replace a panel or infrastructure would cause the payback calculation to be void, and a new calculation would need to be done.

5.3.2. Weather Data

The reported PV capacity gave a result of 19 years; the actual average performance that was recorded gave a result of 20.5 years. This means that external factors and degradation affected the payback period by 7.3%. Weather data such as temperatures (Maximum, Minimum, average and percentiles), solar irradiance and cloud cover are readily available as a public source from the Bureau of Meteorology website (Bureau of Meteorology 2024). However, the recording station may not be close to the area required. Other sources may be obtained through private sources such as an institution that has a constant thermometer setup.

5.3.2.1 Solar Irradiance

Observed Solar irradiance can be easily downloaded from the Bureau of Meteorology (Bureau of Meteorology 2024) as either daily, monthly or yearly values. Defined as the amount of radiant light energy per meter squared, it is an essential component of the energy production of solar panels. The observed solar irradiance, as seen in Figure 4.2, shows a direct comparison with the predicted power output. This was confirmed by the statistical analysis that showed a correlation of 0.84 between the observed solar irradiance and the observed energy output from the carpark data. A multiple linear regression also confirmed a highly significant proportion of energy is provided by solar irradiance. This is not surprising considering the direct relationship given in equation 8. This means that predicting an accurate payback period requires some level of reliable irradiance data to be accounted for.

Weather data is essential to all prediction calculations. As seen by Figures 4.2 and 4.5, the energy output shows a similar pattern to the temperature and solar exposure, i.e. high in summer and low in winter. Climate needs to be considered to ensure a linear energy output since the payback calculations use either an average yearly value or a total yearly value. In the case of unbalanced data such as 2024, an average might be non-representative due to the missing portion of data, for example, if the only data was summer, the average would be inflated, and if they were only winter the data would give a deflated average yearly energy output.

5.3.2.2 Temperature and Climate

Temperature compensation values were given by the specifications. These values (section 4.5.5, Temperature and solar irradiance) show that power and voltage both decrease when there is a large difference between the operating temperature and the temperature of the standard test conditions. These differences are also present in the energy output equation 4.8. This shows that when the operating cell temperature is greater than the standard test condition of 25°C there will be a detrimental effect on the energy output. There is an assumption here that the ambient temperature is always less than 45°C. The smaller the difference between the operating temperature and the ambient air temperature, the less negative effect on the predicted power output. Conversely, in very cold temperatures, the temperature coefficient will be multiplied by a larger value, resulting in low power output (equation 4.8).

Very hot weather will increase the temperature of the cells, causing a decrease in energy production due to the temperature coefficient, as PV cells perform at a lower capacity. However, temperature correlated directly with solar irradiance, which had a greater effect on output. Therefore, Figure 4.2 appears as if temperature correlates with output. Solar irradiance can be affected by the angle of the sun's rays, time of day, and cloud cover, and it also affects temperature, but temperature also relies on the type of surface and humidity. The reflection ability and the moisture on the surface also affect temperature. The two factors can affect each other; for example, a dark surface will absorb more irradiance, leading to a higher temperature. They can also differ late or early in the day when the sun's rays are at an angle, causing less irradiance, but there can still be a high temperature. It is important to account for temperature as it is required for equation 3.8, and it does have a notable effect on power production and, therefore, the payback period.

Figure 4.7 shows very high correlations between energy output, temperature and solar irradiance, with the latter having a higher correlation. This is evidenced in equation 4.8, where there is a direct relationship between energy and irradiance, but temperature varies according to the temperature coefficient and the difference between ambient temperature and photovoltaic temperature.

Temperature can vary by up to 12°C throughout the year on average (Table 4.11). Changing the weather data in the equations shows that these changes can affect the results by up to 89600kW (Table 4.11). This means that the payback period will always be an approximation, as the true value will always vary. The observed carpark data varies by 70573.6kW, showing a difference of 21% between the predicted value using equation 8 and the observed value. This is based on data from only four years; as such, this effect is compounded with higher payback periods as there are more weather cycles that will affect the result, so a 20-year payback will vary more than a 3-year payback.

5.3.2.3 Seasonal Variability

Energy output varies by season. The raw energy output data, as plotted in Figure 5 clearly shows a sinusoidal pattern across the years, high in summer and low in winter, and that temperature and solar irradiance follow a similar pattern. An analysis of variance shows significant interaction for energy output between month and year. This shows that the effects of months can vary from year to year. This is typical of observed weather patterns, no two years are the same, for example sometimes July is warmer than June and vice versa. This relationship is confirmed by the predicted energy output as shown in Figure 4.2. It can also be seen in Figure 6 that the monthly averages for each factor show similar high and low for seasons, but there is some variation within the seasons.

Payback period in terms of years, relies heavily on the total annual energy output. It is known that weather has strong yearly effects (CSIRO 2024). Using a data set that is limited to five years shows only information that is relevant to those five years and cannot inform other years. The predictions should be updated regularly to allow for seasonal and yearly changes. Table 4.10 shows the long-term averages for temperature and irradiance and the percentage changes in the five years of data. Although the observed temperature and solar irradiance over the five years of the data was within 7% of the long-term averages (Table 4.10), the observed carpark data was highly variable, especially in the winter months. One possible reason is that the five years had warmer than usual winter nights. Another reason is that the predicted values in Table 4.10 do not account for the tilt angle of the carpark data. As discussed in section 4.5.5, adjusting for panel peripherals, the tilt angle changes the amount of solar irradiance in winter when the sun is lower, therefore creating higher than predicted energy in winter as shown in Table 4.10.

When looking at the observed carpark data it must be noted that some of the data in incomplete. In 2024, the average output would not be representative since the data used stops in October. There are also missing values within all factors. The payback period presented in this study is conservative and needs to be read in conjunction with error. Also note an obvious section of low energy output in early 2023 as shown in figures 4.5 and 4.8. These values need to be investigated and possible removed from the analysis.

5.3.2.4 Extreme Weather and Degradation Risks

The average rate of extreme weather, including hail, lightning, heatwaves, snow and flooding, varies greatly from region to region. Storm events that can cause damage, such as heavy storms, will increase the amount of maintenance and decrease the amount of operating time depending on the severity of the repairs. Meanwhile, weather events such as snow and heat waves will affect the temperature of the system; see the temperature coefficient for the effects of that. Finally high rainfall and flooding can cause damage as well as accelerating degradation and aging as electrical components corrode. Extreme weather needs to be considered if in an area with a high level of one or more of these factors (high rainfall in coastal areas, etc) and degradation may need to be adjusted for this.

Other factors can affect degradation rates as well, including the combination of components used, amount inverters replacements needed and battery degradation for systems to which that applies.

5.3.3. Financial Data

The payback period is heavily reliant on the value of the energy that is produced. The initial calculations have used the values as reported by the data provider. Without an accurate value, the payback calculations can be misleading. In Australia, the cost of electricity can vary significantly (Australian Energy Regulator 2024), and there is no guarantee that the values will be valid. The calculations reported in this study have used a static value per kWh and an inflation of 5% in Tables 4.8 and 4.9, which also show the lowest payback years. The inflation value has caused the largest difference in the payback period (a decrease of 16%). This was based on a simple calculation that involved constant inflation value but did not allow for changes in inflation and/or market values. It is essential to update the calculations regularly to compensate for these changes.

5.3.4. Parameter Priority

If a user requires a simple payback period calculation for a manual method, only a few parameters will be selected. Therefore, determining which assumptions and parameters have the greatest impact on the accuracy of payback period estimates is needed. Weather and seasonal variation play a major role in the energy production due to temperature, number of hours of sunlight and solar irradiance. However, during a year, the total energy output needed for the payback period calculation involves the total annual values. Yearly factors such as degradation will play a greater role in the yearly values and therefore the payback period. Above all of the parameters, the financial information is vital to the payback period calculation. The energy output fluctuates for seasons while slowly degrading at the same time, and the cost of energy can rise, so over time, less energy might not be equated with less cost. This was clear in Table 4.9, where the energy output decreased due to degradation, but the cost increased due to inflation, resulting in the shortest payback period.

5.4. Method Analysis

Regular analysis of methods is important as technology, human understanding, and resources for calculations continue to evolve. Different users require models with differing focuses. To discuss the usefulness of methods, it is essential to consider both the accuracy of the results and their accessibility. Part of this research is determining the limitations and trade-offs between accuracy and simplicity. Therefore, versatility will also be evaluated; in this context, versatility means the combined ability to be accurate and easy to use. This can also be used to determine which types of users benefit the most from specific types of payback models.

5.4.1. Models Focused on Accuracy

Theoretically, software such as HOMER could be more accurate if the forced changes made by the program are applied. HOMER forced the addition of a battery and converter component due to its primary function as a hybrid simulation tool. Therefore, if these systems are integrated, the software in question might achieve greater accuracy than when compared to the current tests completed in this study. However, this cannot be determined with the current data. Furthermore, if these modules are unavailable, attempting to estimate payback with a program that compels the user to add non-existent components would not yield more accurate results than other methods. The other software, SAM and RETScreen were found to be better for payback analysis specifically.

Manual methods have the highest potential for accuracy, depending on the factors applied and the quality of the data. However, they can also be the least accurate if the simplest methods are employed. For manual methods, accuracy is determined by the amount of time and complexity the user decides to invest.

The payback period will be the most accurate when the predicted power output is also the most accurate. Higher accuracy is achieved when more known parameters are available to add to the energy model. Solar irradiance plays a major part in predicting energy output; having access to high-quality irradiance is essential to providing more confidence in energy predictions. Similarly, this study has shown that incorporating the tilt angle provides more accurate conversions of solar irradiance and thus higher accuracy.

5.4.2. Models Focused on Accessibility

Some software costs money while some are free. Most software types that do cost money offer a free version of a limited time which may be an option for user who only want to use the program once. While some are intuitive in basic use they all offer challenges. HOMER forces the user to apply components that may not be available. SAM in general has a difficult user interface. RETScreen's free version does not allow the user to save their progress and so any calculations need to be performed in a short amount of time. Other software such as macros may be difficult for people with limited IT skills, and the one tested, PC3D, was unable to provide a payback period result in the end.

The manual methods are accessible; however, this can change depending on the methods used. Data can be difficult to find depending on region and other software such as excel may be required to effectively use certain methods. Simply put, the more accurate a manual method the more complex and therefore the less accessible it becomes.

5.4.3. Models Focused on Versatility

Versatility refers to how adaptable a method is to many different functions. Manual methods are the most versatile since they can be changed to best suit the user and their situation. The accuracy will vary, but the accessibility is quite high. For software, the versatility is also high when considering that they can be used on most computers and can be adjusted using the program and not manually. HOMER can only be used on one computer, however, and the demo version of RETScreen can't save progress, so that lowers the accessibility due to the high cost of the software. SAM can be installed on multiple computers and doesn't have either of these restrictions; however, its user interface is more complex. For accuracy, apart from forcing the user to adapt certain modules, HOMER is still the most widely used for energy simulations. RETScreen and SAM are more suited to payback calculations and provided accurate results like the simple payback period manual method. Other software such as PC3D were complex and not suited for the task of calculating payback period. For a user who isn't well educated about PV systems and simply wants to calculate the payback period, these more complex systems are naturally less suitable for this type of user.

5.5. Different Tools for Different Users

The assessment of accuracy, accessibility and versatility presented in this study can be a valuable tool in the decision-making of users. A homeowner who wants to buy a small, simple PV system for their home rooftop or garden would likely settle for the payback given to them by their supplier. They would use the information on payback as a tool to decide if purchasing a solar system is beneficial. This simple payback would likely be calculated with the stats from the PV panel data sheet, estimating annual energy produced and deducting that from the energy the household uses to estimate savings. On the other hand, an employee from a professional industry will have a method granted to them by their supervisors and/or company. They would source a professional with a greater understanding of PV and likely use payback as a project planning tool rather than a decision-making tool.

The users that benefit the most from a variety of payback period methods are users who need a larger, more complex system but aren't PV experts themselves. An example of this would be a librarian who wants to install a solar array for the public library where they work. To do this, they would need to submit a proposal to the city council, and part of that proposal would need to be the payback period. The user in this case can't use a simple payback model but does not have the tools or prior experience that the most complex methods require. This research provides the most benefit to these types of users.

5.6. Conclusion

5.6.1. Conclusion of Research

Various methods for calculating payback, including both software and manual methods, were evaluated to determine usability, complexity and accuracy. The effects of different environmental and economic factors were also analysed to determine their importance and impact on the results. Each method tested (HOMER, SAM, RETScreen, PC3D and the manual methods) showed differing levels of complexity, accessibility and feasibility as a payback period method. While there are unique attributes that each method brings, there are collections of trends and insights that may be of interest to researchers and industry.

Most importantly, the results show that manual methods offer a variety of benefits when calculating a single value. While software may provide better coverage for a full analysis of everything the system has to offer. Payback period calculations specifically and on their own are better suited for manual methods, which are comparable to software while being more reliable and less complex. When used in small-scale or early-stage planning (which is when the payback period is most often performed) it is more feasible to perform a simple manual method than to download a software package. Manual methods allow the user full control over the assumptions and data used, which improves confidence in the result and reduces the risk of incorrectly entering values or using incorrect default values embedded in the software tools. Assuming the core input variables, such as system cost, annual energy production, and local electricity rates, can be collected by the user manual payback period estimation would be the preferred option for most.

The commercial and academic software tools tested do have some benefits. Some have detailed modelling environments that can estimate system behaviour over time, such as degradation and weather effects. If in the early stages of planning a system, these tools might provide additional benefits outside of the payback period, such as selecting additional modules, such as inverters and batteries, or even mounting systems. They could even help the user select the best type of PV for their situation. However, they also come with steep learning curves, complex interfaces, default assumptions, inconsistent support for local data, and restrictive software licensing. Also, most of these systems are designed for larger, industrial or community-based systems, making them less desirable for smaller, household-scale PV systems.

The assumptions and parameters used in calculations were also found to differ in importance. Solar irradiance was the most important, as it is the amount of solar energy a system is exposed to that determines the energy produced. This directly determines annual energy output, giving it a linear effect on annual savings and revenue. Therefore, accurate irradiance data is important for weather predictions if considered. Other important factors included degradation, temperature and change in the value of electricity. The complexity involved in using these factors when calculating payback varies depending on the data and mathematical techniques available to the user. Some software tools support some of these parameters either by default or via request. Manual methods can apply all of these at the user's discretion however some may be more difficult to find data for then others. This also differs depending on locations as some areas have more detailed weather and electricity analysis than others.

The comparison also showed the balance between complexity and usability. Looking at payback exclusive software can be highly complex with high usability while manual analysis has a tighter scope but is generally less difficult to perform. Individual consumers, installers and potentially policy makers may prefer a manual analysis when assessing the financial risk.

5.6.2. Limitations

One major limitation of this method is a general lack of inclusivity. There are many methods for calculating payback period and time, and this process only tests a few. Another limit is the fact that none of the software types tested are designed specifically for payback period, except for the manual analysis. The software types used are all meant for general analysis of renewable energy systems, with payback simply being a feature. However, when it comes to large-scale PV projects, these are the tools used to determine payback, along with several other factors. The fact that most of the tools used are not designed for payback needs to be considered further. Would it be worth creating a new tool for this one purpose when other tools perform this function alongside many others?

There were limitations with the tests and analysis performed. The scope of software covered only three commonly used types and one more obscure tool. There are many other modelling tools and hybrid methods, some of which integrate new technology such as machine learning and AI, that may offer unique techniques that have not been evaluated but are outside the scope of this study. Another issue is that the data used for energy production, cost, and local conditions were taken from a variety of sources and were not collected specifically for this study. There were also assumptions that, while realistic, were not completely accurate, such as inflation and degradation (degradation of the panels was known, but not how much they had degraded before data was collected).

Pricing models and financial factors such as taxes, interest rates, and other variables cannot be fully addressed, as these can change based on region, the global energy market, and overseas policies. No data on discounted payback period metrics or NPV, and limited financial analysis. While the software may be able to adjust for this to an extent, the manual methods cannot. Manual methods also did not account for many different time-varying system behaviours or accurate degradation; they simply used an average rate provided by panel sheet data. Also, a user's ability to collect and correctly input necessary information was assumed, which may not always be true in practice.

5.6.3. Future Directions

Due to the varied results, it would be beneficial to test more software tools if possible. This includes emerging solutions like open-source platforms or mobile applications for homeowners and small business owners interested in installing a PV system. A wider range of locations would also be beneficial; investigations on how different methods perform across various regions and climates could add extra insight.

Hybrid approaches could also be used to see if the versatility of manual methods can be boosted by software through the visualisation of data and automated calculations. While difficult to account for across the globe, investigating ways to include time-based financial analysis could also help users whose main concern is cash flow.

It may also be useful to incorporate user experience testing. Including different types of users such as engineers, consumers and policy makers. Seeing how each would theoretically interact with different methods and evaluating ease-of-use and if needs were met. A more comprehensive view of parameter sensitivity, especially for more complex systems, would also allow better understanding of which factors are more important to include in testing as well as decreasing the uncertainty of results.

5.6.4. Final Remarks

The different payback period methods meet the practical needs of PV users by highlighting context, purpose, and user skill level in their calculations. This study has revealed that for PV users, the appropriateness of the payback period method is less influenced by technological advancements and more by access to data and the technical skill of the user.

For small to medium-scale PV systems, manual calculations are preferred due to their simplicity and reliability, providing an easy method for users who may not have extensive technical training. Larger industrial systems benefit more from complex software for calculations. This complexity is justified because payback period calculations represent only one of many financial metrics considered by professionals who usually have specialised training in the chosen methodology by their organisation.

In all cases, high-quality, location-specific data is important for accurate estimates and meaningful conclusions. Transparency and simplicity are crucial, ensuring that the approach used for payback calculations is accessible, reliable, and controlled by users to support informed decision-making regarding energy solutions.

The research question was “How do different payback period methods meet the practical needs of photovoltaic (PV) users?” It was found that transparent methods that allow for both complex and simple equations that can operate with a limited amount of data while also accepting any additional user-contributed information are what is most desired. A manual method suits these needs however may still be intimidating for certain users. Recent developments have a limited effect on payback, however the requirements for estimating energy output for systems such as TPV and QDSC can be widely different, as they use vastly different processes to generate energy and therefore would require different calculations and data than what was tested in this study. The assumptions and parameters that have the greatest impact on payback are solar irradiance and changes in the cost of energy over time, so for a simple but accurate calculation, these are the parameters that should take priority in the choice of payback calculation. Manual methods prove to be the more transparent and customisable option; however, software often allows the user to access data and processes they may not be familiar with. Private users installing a small system benefit the most from a simple payback that uses the system specifications and either savings based on the reductions from their current energy bill or revenue from a planned payment plan. Industry personnel benefit from partnerships with specific software that they can use to receive training. Meanwhile, non-PV experts who wish to install a more complex system may need to look at their options and find one with a balance between accuracy and simplicity. The trade-offs between those two are simple; accurate calculation methods are often more complex as they require more steps, more data and more complex calculations, some of which can only reasonably be performed by software. Meanwhile, simple methods are easier for non-experts but may not account for enough of the parameters to be considered fully accurate. It is important to note, however, that since the payback period is a predictive model it will always be classified as an estimation. Some users only need a rough estimate to decide on financial feasibility, while others, typically those planning larger, more expensive systems, will need an estimate with a much smaller margin of error.

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APPENDICES

6.1. APPENDIX A: HOMER

The following is a detailed description of how to use the HOMER software. It includes a step-by-step set of instructions along with screenshots of the software. No captions are used as the screenshots lie within their description.

Design input specifications from left to right are:

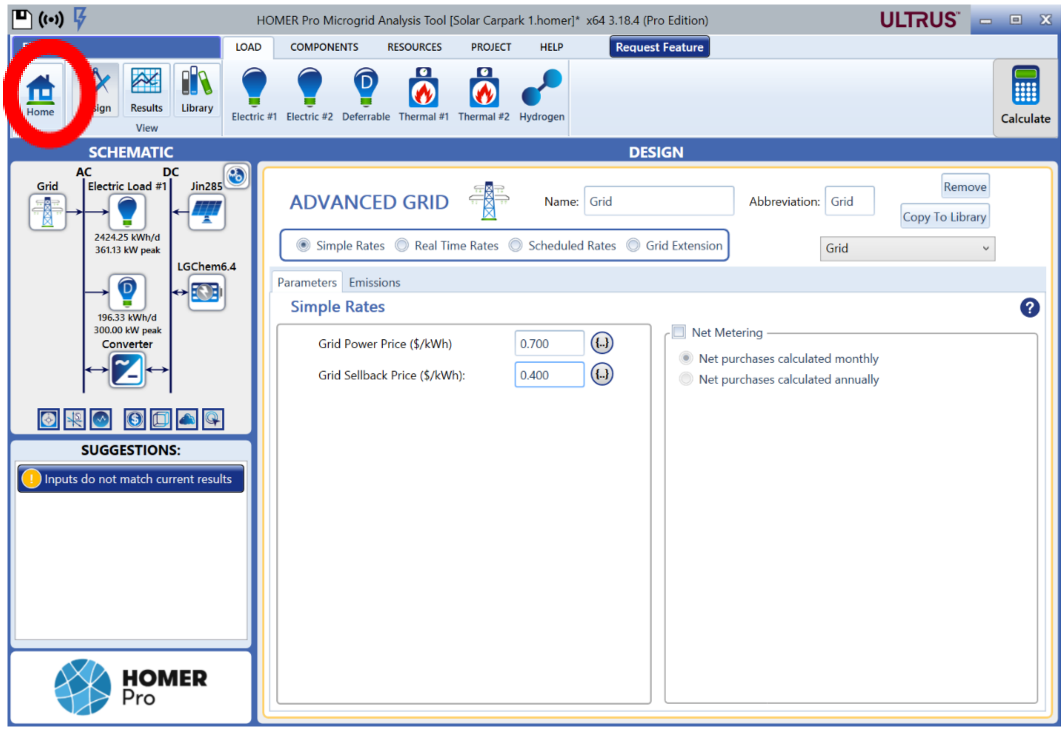
If you have not started a project before, choose setup assistant, then use the map to find your location.

1. Select “Grid” from the schematic and manually input the electricity prices.
2. LOAD: The average monthly use from our data was input as the monthly electricity load. Use the Add/Remove table to add each type of load. Add in the information for the converter, 19 x Sunny-power 60 inverter. These were put in as battery (ABB Flywheel 60) and converter (ABB MGS100) using a search. Each component has an input box for the cost. Fill these in using the values given for the inverters.
3. COMPONENTS: Panel specifications Jinko Solar JKM-285M-60 can be input by searching the database under the tab labelled Add/Remove. Fill in the costs of the panels in the cost box.
4. CALCULATE: When all items have been input use the calculate button to run the simulation. This button must be selected after each design change.
5. Weather data needs to be in a specific format and only a single year.

Design parameters

How much would it cost to buy electricity from the grid and how much does the system sellback for?

This example is assuming 70c cost and 40c sellback (70%)



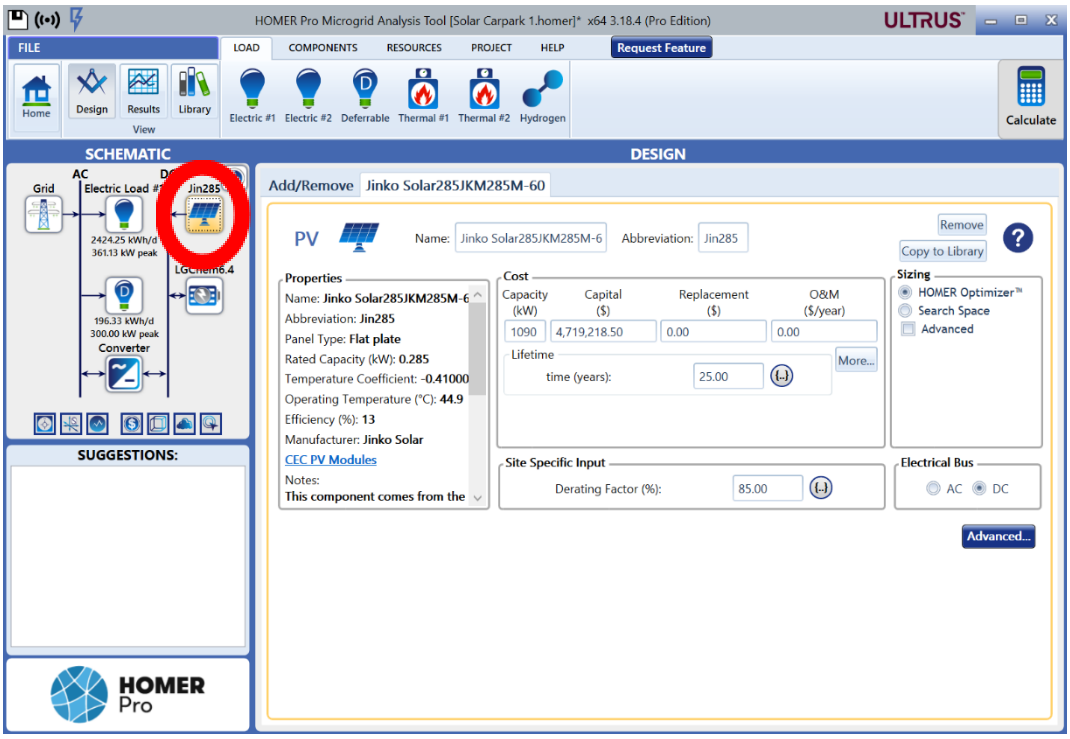
Input Electric Load based on the data

Hour	Load (kW)
0	30.000
1	30.000
2	30.000
3	30.000
4	30.000
5	30.000
6	30.000
7	100.000
8	200.000
9	200.000

Metric	Baseline	Scaled
Average (kWh/day)	2,424.2	2,424.2
Average(kW)	101.01	101.01
Peak (kW)	361.13	361.13
Load factor	.28	.28

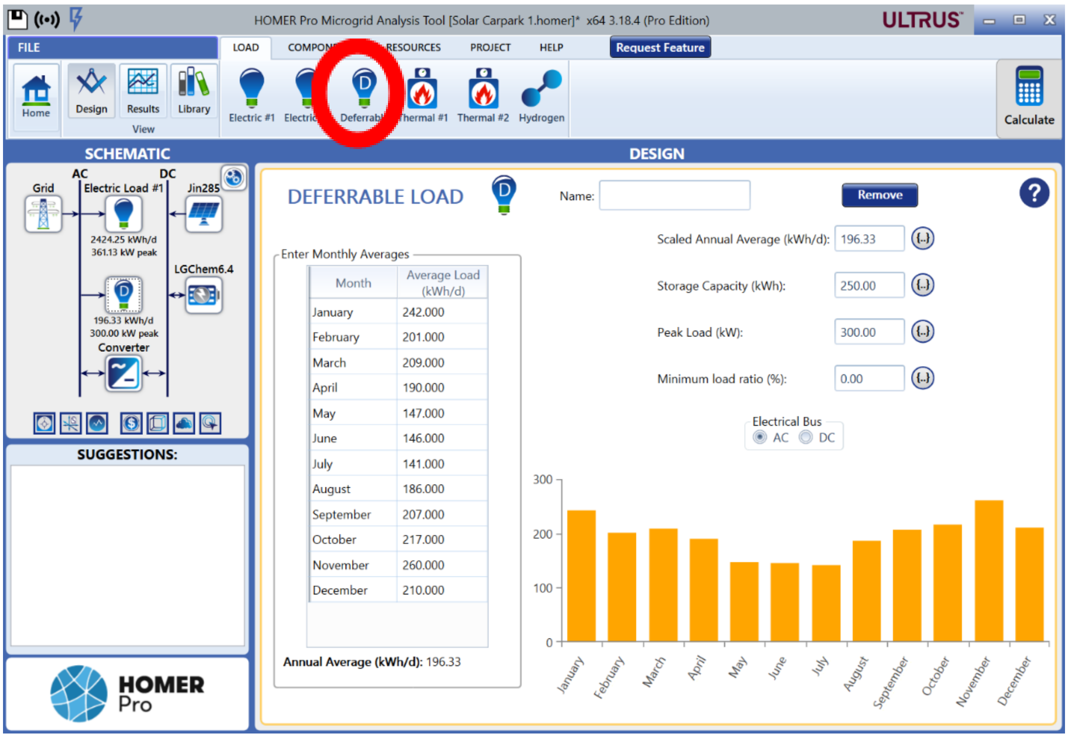
Our system

Put in the components: Jinko 285, capacity of 1090kW, and total cost of $4719218.50



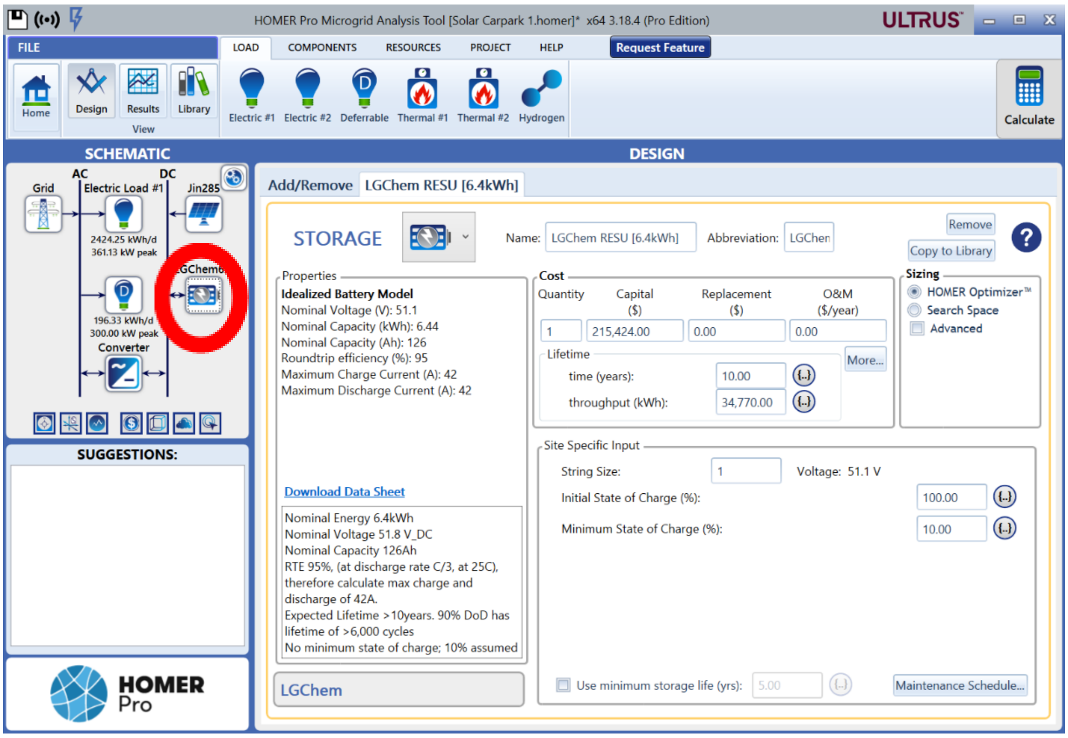
Deferable load

The input are the monthly averages from the CarPark data



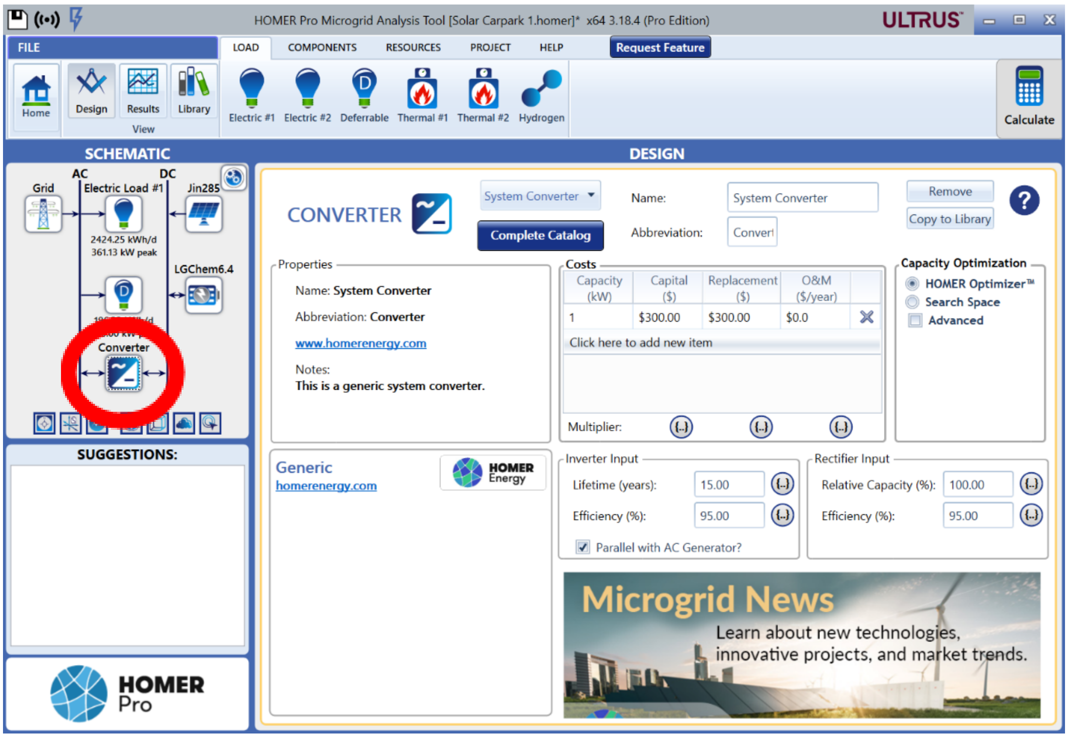
Storage

Battery specification for LGchemRESU and price of $215424.00

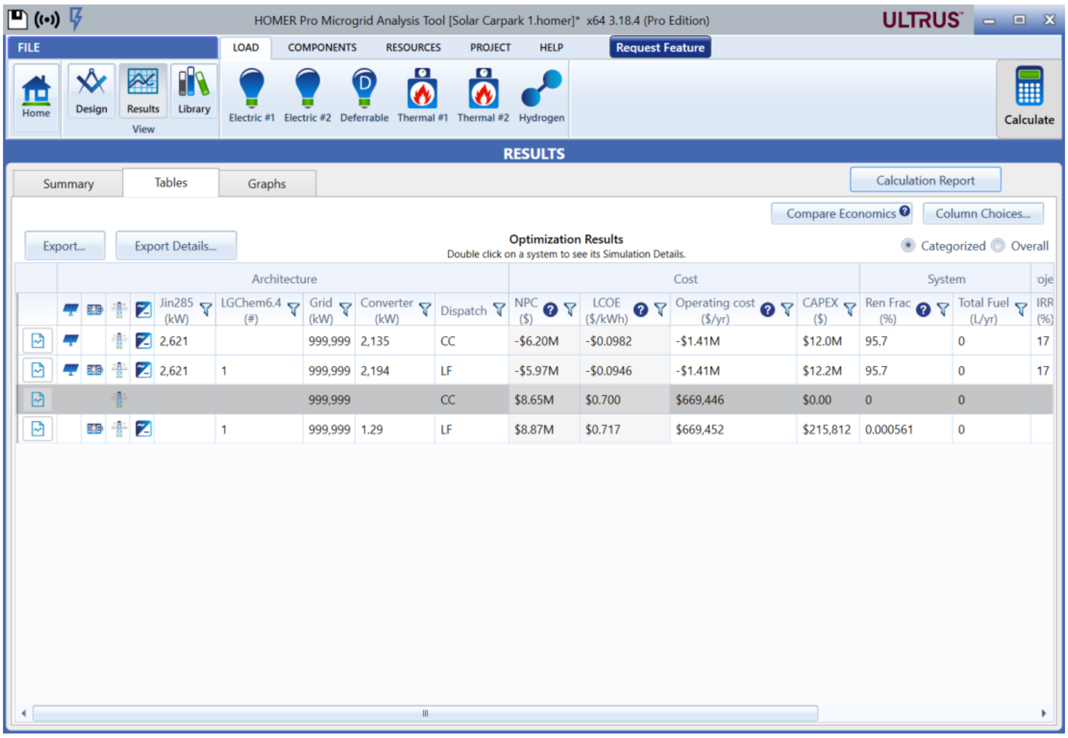


System converter

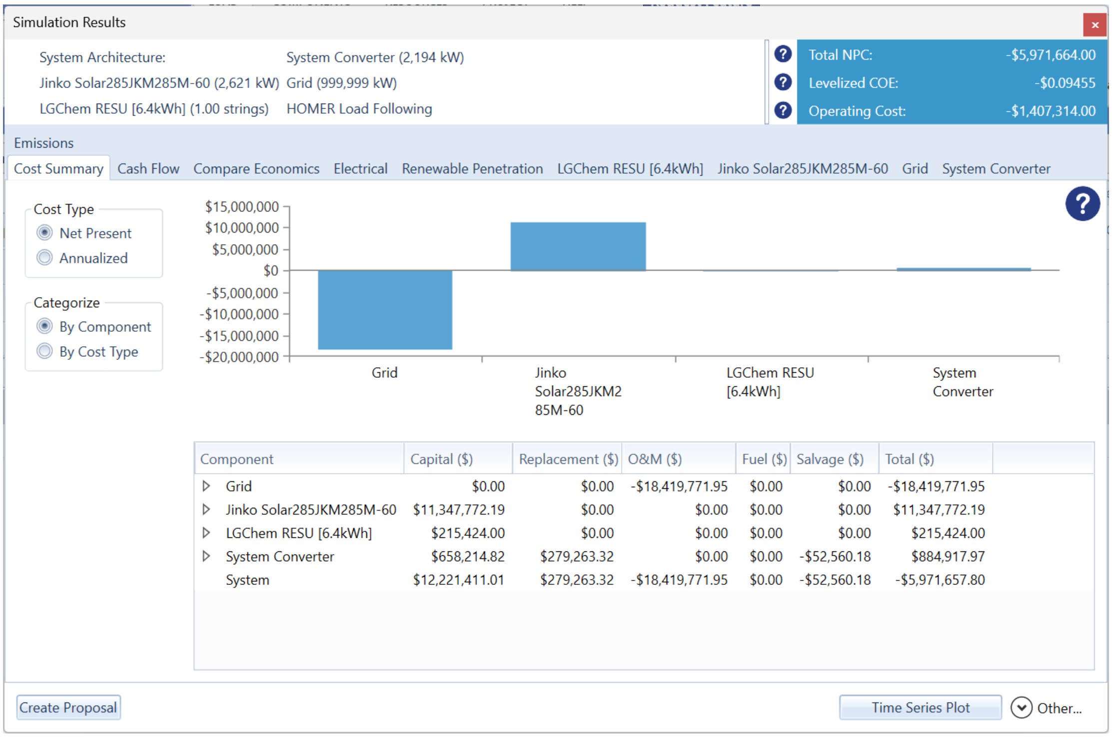
Unknown, this is a generic setup



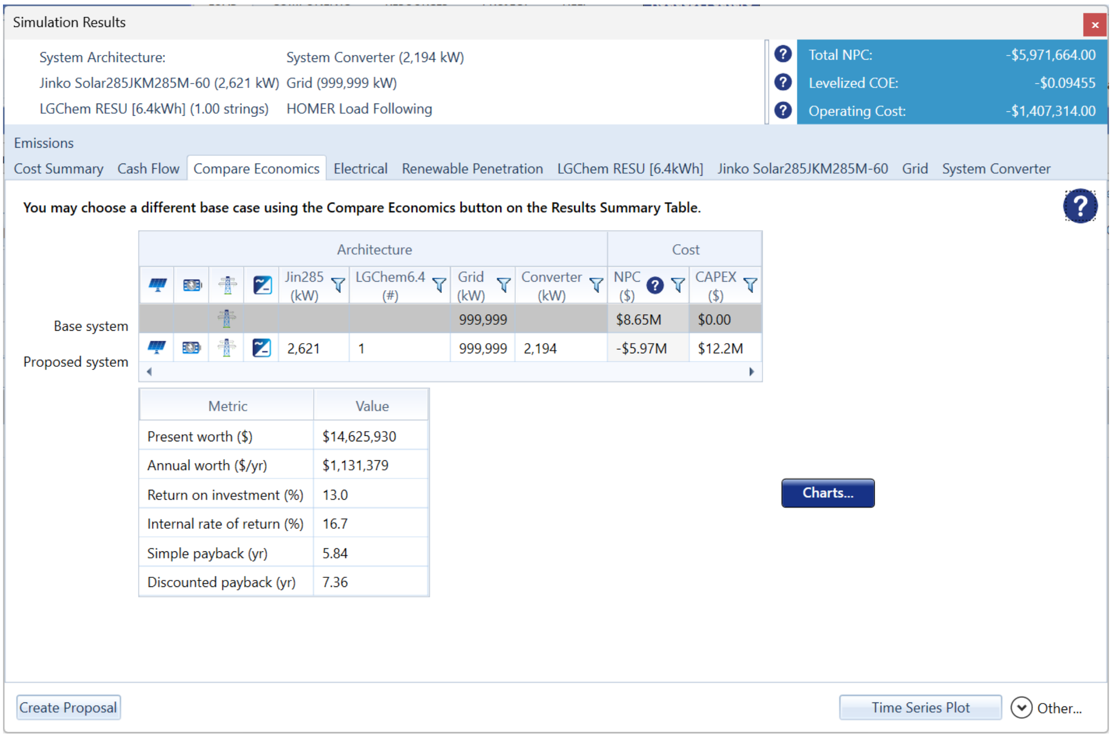
After inputs are finished, click on Calculate (upper right hand side), the following scenarios are given



1656 Select the second one (that has all of the components)



1657 Simple Payback using the assumed inputs



6.2. APPENDIX B: SAM

The following is a step-by-step set of instructions in the use of the SAM software. Firstly there are written instructions followed by screenshots of the software. No captions are present on the screenshots as they are contained within the set of instructions.

Select Photovoltaic and then Single Owner from the list of options. The components are selected by moving down the list of options in a panel on the left-hand side.

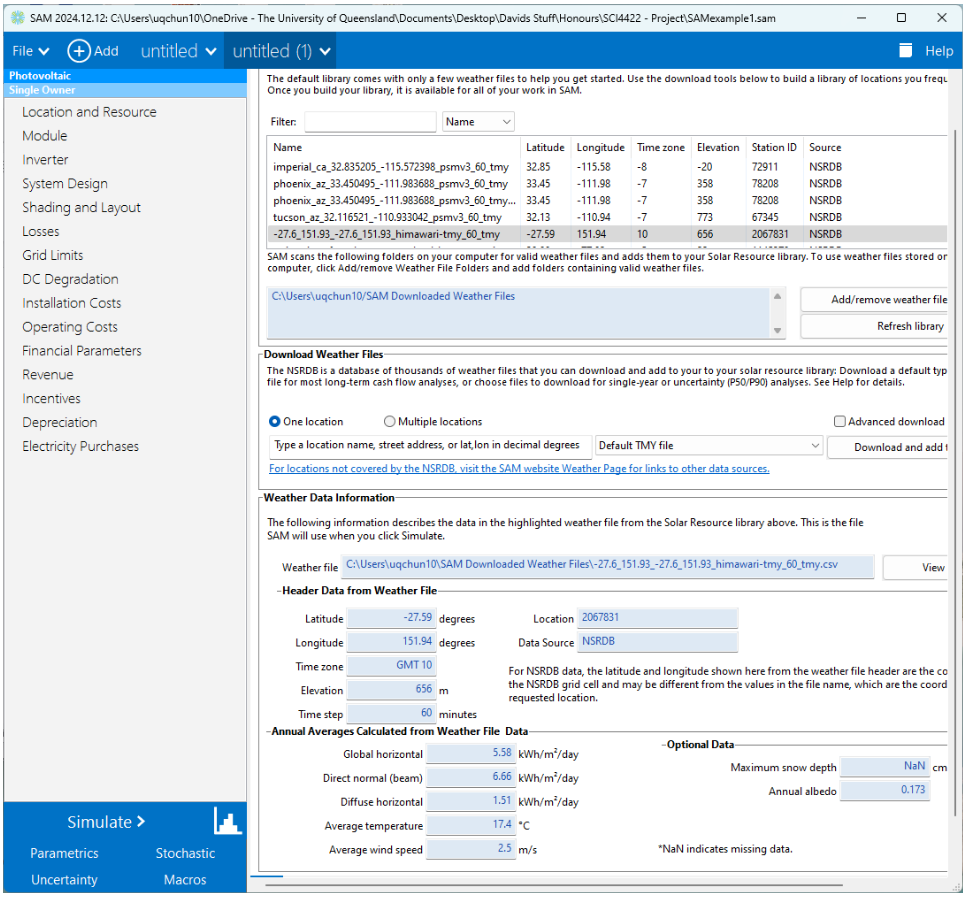
By inputting the longitude and latitude coordinates, SAM will search for the weather using a file system that doesn't appear to be able to be input as a CSV file. The next item on the list is to input the module, search for the required Jinko Solar 285M, using the user defined options, change any of the parameters as required and input the number of solar cells.

Following the list, search for the Sunny-Power 60 Inverter; SAM relies on data from each manufacturer, assuming no modifications have been made.

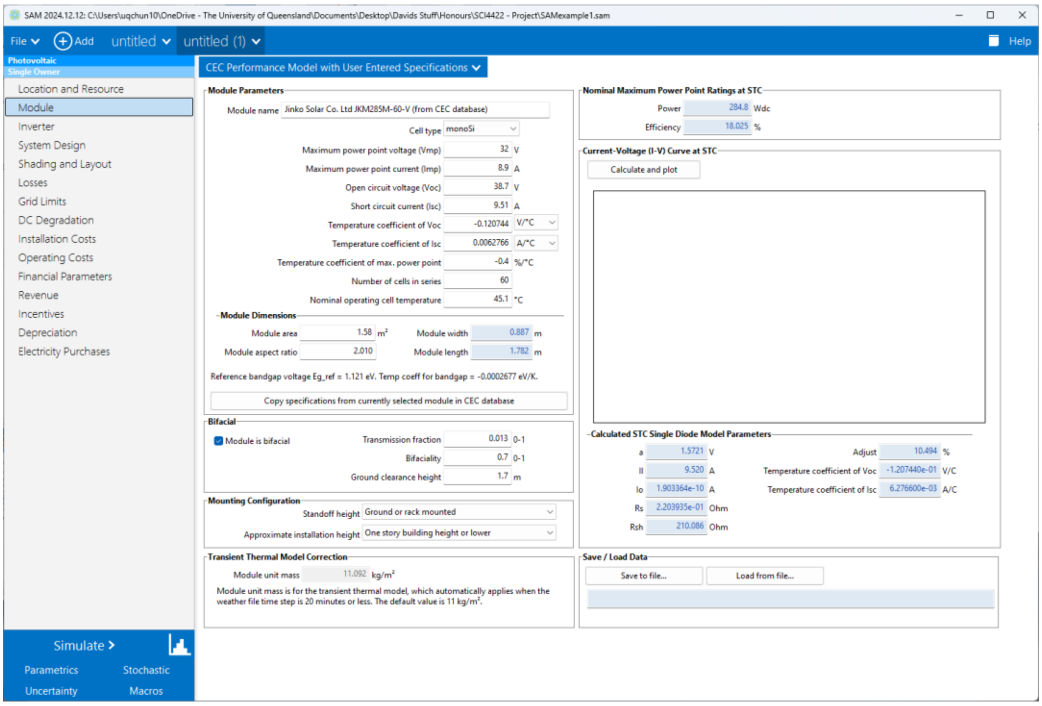
There are a lot of comprehensive options for inflation depreciation etc and the user can choose to either use the defaults or input their own. The cost of the system doesn't seem to be able to be inputted, instead SAM calculates it from the specified modules. This is the price today not the price in 2017 when our panels were installed. Run the analysis to determine the payback period.

SAM inputs and outputs click on each of the options from the list on the left hand side

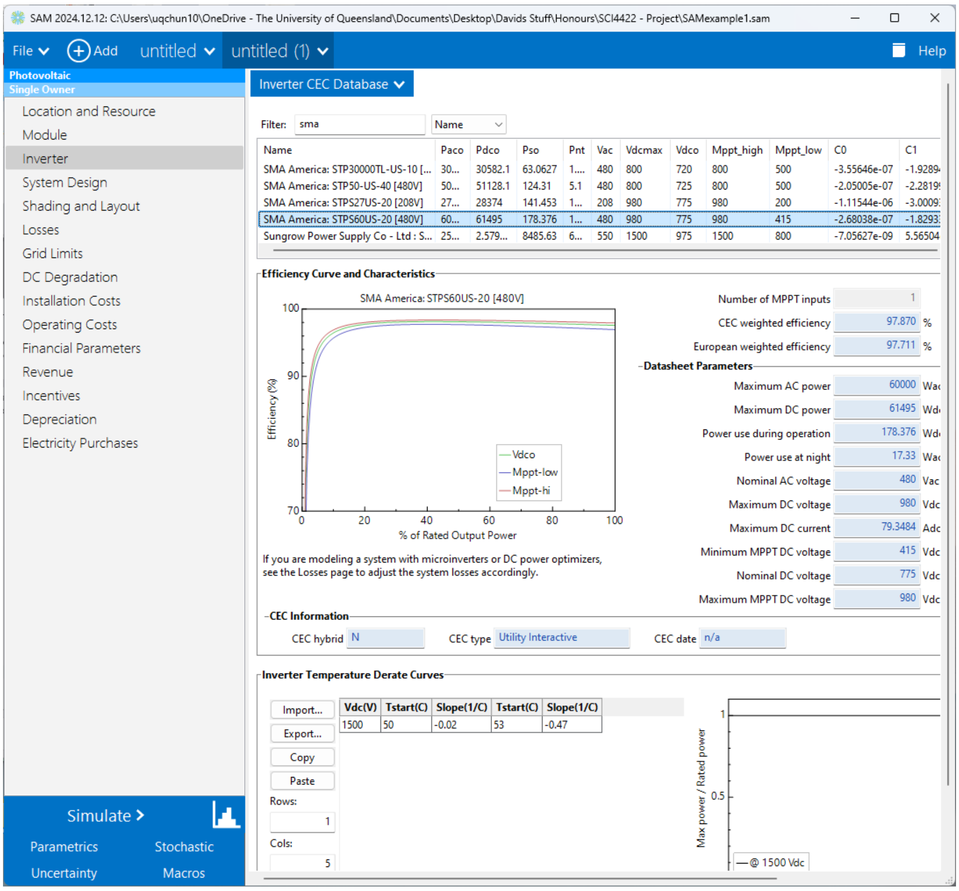
Location and Resource: Climate Data



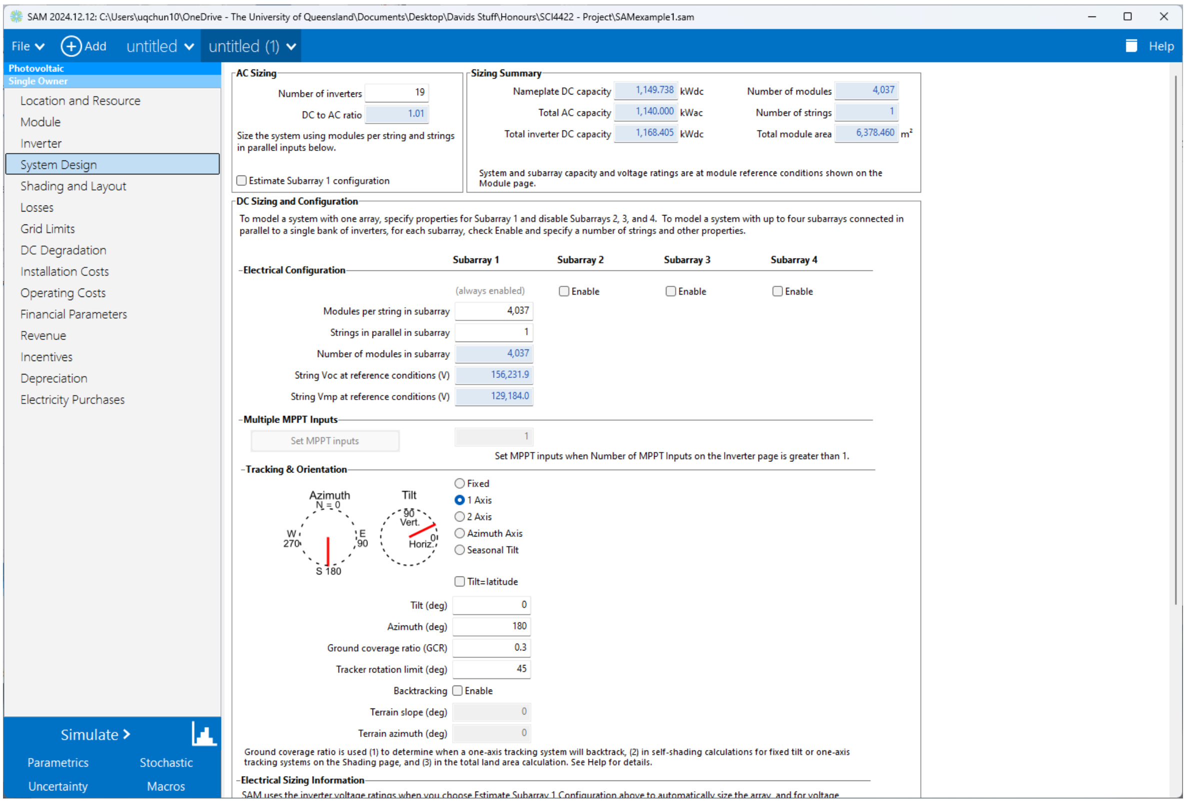
Module: Select user entered specification, search for the jinko Solar panels, input the specific information.



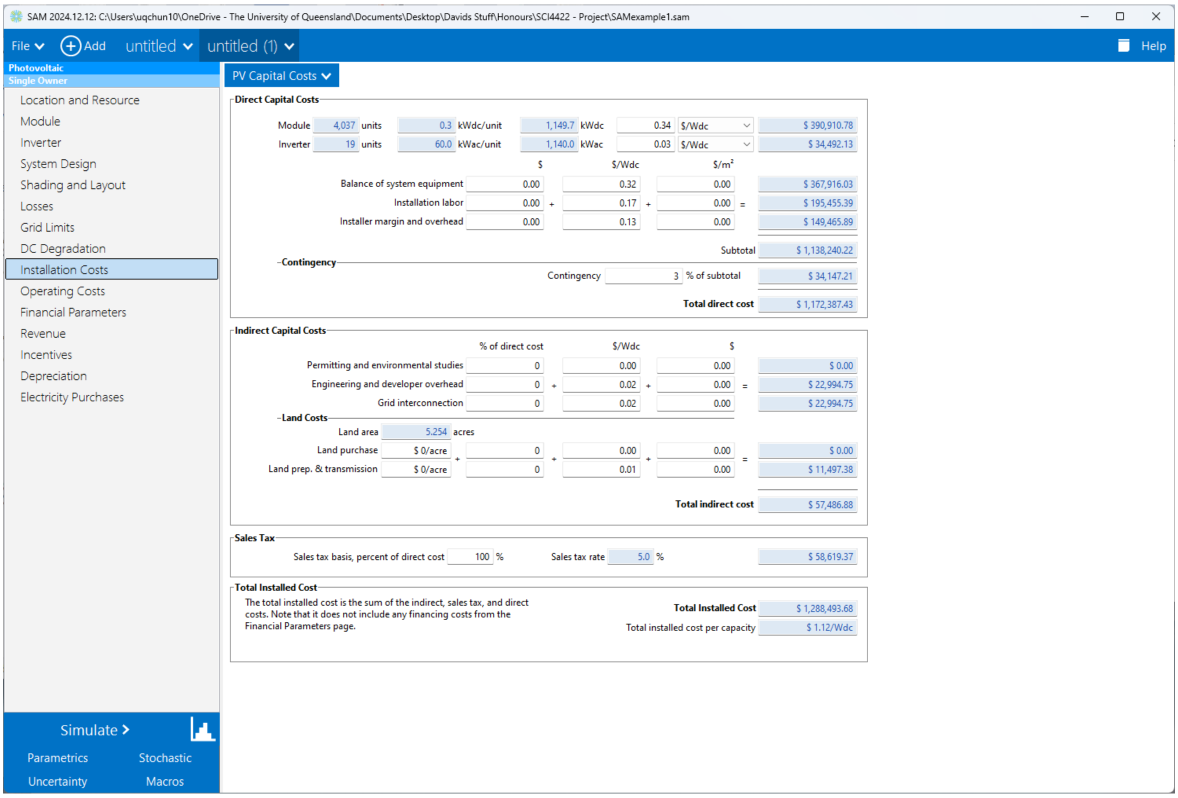
Inverter: select the required inverter from the list, the specifications are automatic.

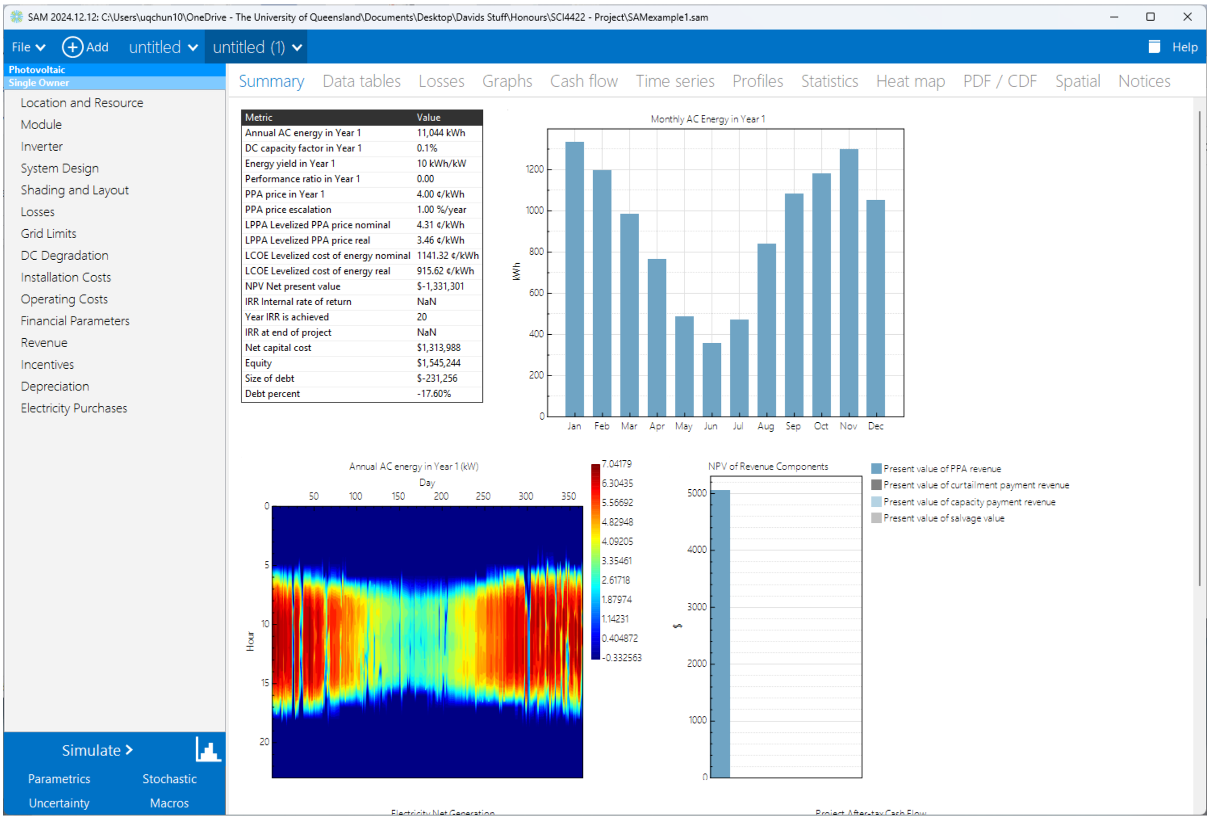


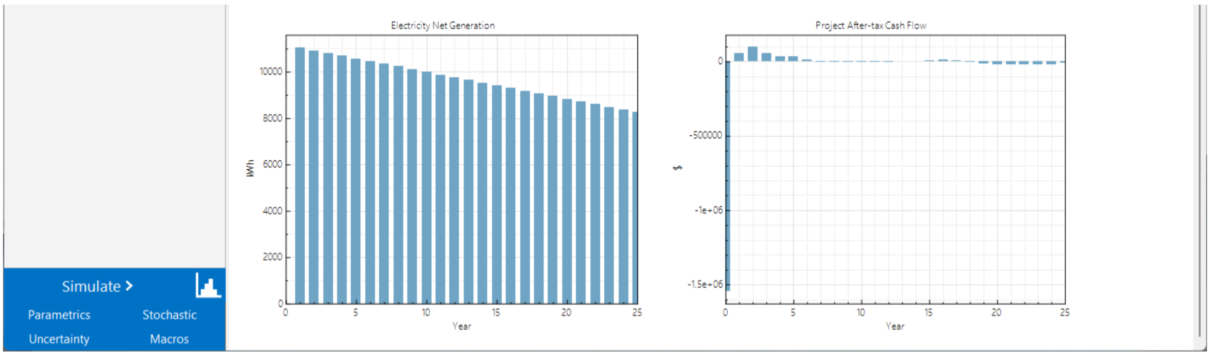
System Design: manually enter values for 19 inverters and 4037 PV panels.

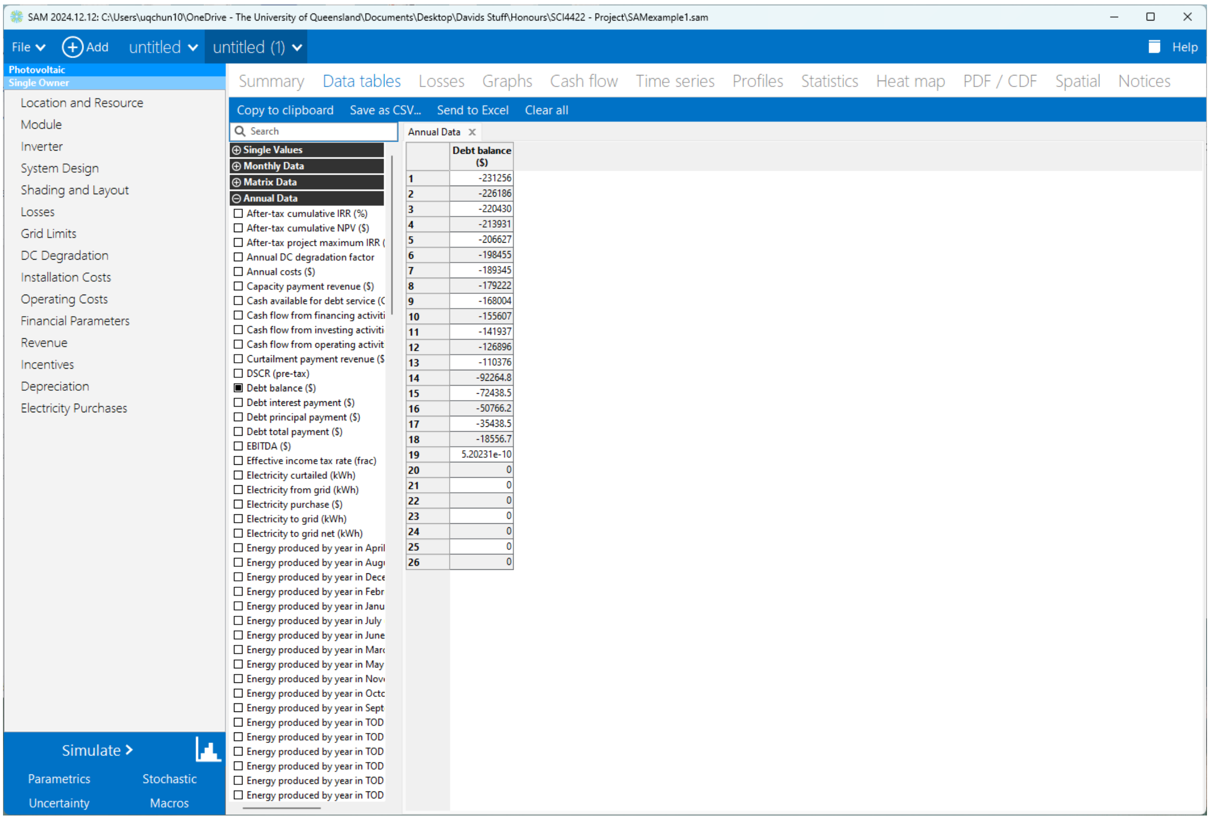


Installation costs are generated based on the modules you selected




SAM 2024.12.12: C:\Users\uqchun10\OneDrive - The University of Queensland\Documents\Desktop\Davids Stuff\Honours\SCI4422 - Project\SAMexample1.sam
File
Add
untitled
untitled (1)
Help
Photovoltaic
Single Owner
Summary
Data tables
Losses
Graphs
Cash flow
Time series
Profiles
Statistics
Heat map
PDF / CDF
Spatial
Notices
Location and Resource
Module
Inverter
System Design
Shading and Layout
Losses
Grid Limits
DC Degradation
Installation Costs
Operating Costs
Financial Parameters
Revenue
Incentives
Depreciation
Electricity Purchases
Simulate
Parametrics
Stochastic
Uncertainty
Macros
Metric | Value
Annual AC energy in Year 1 | 11,044 kWh
DC capacity factor in Year 1 | 0.1%
Energy yield in Year 1 | 10 kWh/kW
Performance ratio in Year 1 | 0.00
PPA price in Year 1 | 4.00 ¢/kWh
PPA price escalation | 1.00 %/year
LPPA Levelized PPA price nominal | 4.31 ¢/kWh
LPPA Levelized PPA price real | 3.46 ¢/kWh
LCOE Levelized cost of energy nominal | 1141.32 ¢/kWh
LCOE Levelized cost of energy real | 915.62 ¢/kWh
NPV Net present value | $-1,331,301
IRR Internal rate of return | NaN
Year IRR is achieved | 20
IRR at end of project | NaN
Net capital cost | $1,313,988
Equity | $1,545,244
Size of debt | $-231,256
Debt percent | -17.60%
Monthly AC Energy in Year 1
kWh
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Annual AC energy in Year 1 (kW)
Day
Hour
7.04179
6.30435
5.56692
4.82948
4.09205
3.35461
2.61718
1.87974
1.14231
0.404872
-0.332563
NPV of Revenue Components
Present value of PPA revenue
Present value of curtailment payment revenue
Present value of capacity payment revenue
Present value of salvage value


Simulate
Parametrics
Stochastic
Uncertainty
Macros
Electricity Net Generation
kWh
Year
Project After-tax Cash Flow
$
Year



SAM 2024.12.12: C:\Users\uqchun10\OneDrive - The University of Queensland\Documents\Desktop\Davids Stuff\Honours\SCI4422 - Project\SAMexample1.sam
File
Add
untitled
untitled (1)
Help
Photovoltaic
Single Owner
Location and Resource
Module
Inverter
System Design
Shading and Layout
Losses
Grid Limits
DC Degradation
Installation Costs
Operating Costs
Financial Parameters
Revenue
Incentives
Depreciation
Electricity Purchases
Simulate
Parametrics
Stochastic
Uncertainty
Macros
Summary
Data tables
Losses
Graphs
Cash flow
Time series
Profiles
Statistics
Heat map
PDF / CDF
Spatial
Notices
Copy to clipboard
Save as CSV...
Send to Excel
Clear all
Search
Single Values
Monthly Data
Matrix Data
Annual Data
After-tax cumulative IRR (%)
After-tax cumulative NPV ($)
Annual DC degradation factor
Annual costs ($)
Capacity payment revenue ($)
DSCR (pre-tax)
Debt balance ($)
Debt interest payment ($)
Debt principal payment ($)
Debt total payment ($)
EBITDA ($)
Effective income tax rate (frac)
Electricity curtailed (kWh)
Electricity from grid (kWh)
Electricity purchase ($)
Electricity to grid (kWh)
Electricity to grid net (kWh)
Annual Data
Debt balance ($)
1 -231256
2 -226186
3 -220430
4 -213931
5 -206627
6 -198455
7 -189345
8 -179222
9 -168004
10 -155607
11 -141937
12 -126896
13 -110376
14 -92264.8
15 -72438.5
16 -50766.2
17 -35438.5
18 -18556.7
19 5.20231e-10
20 0
21 0
22 0
23 0
24 0
25 0
26 0

1682

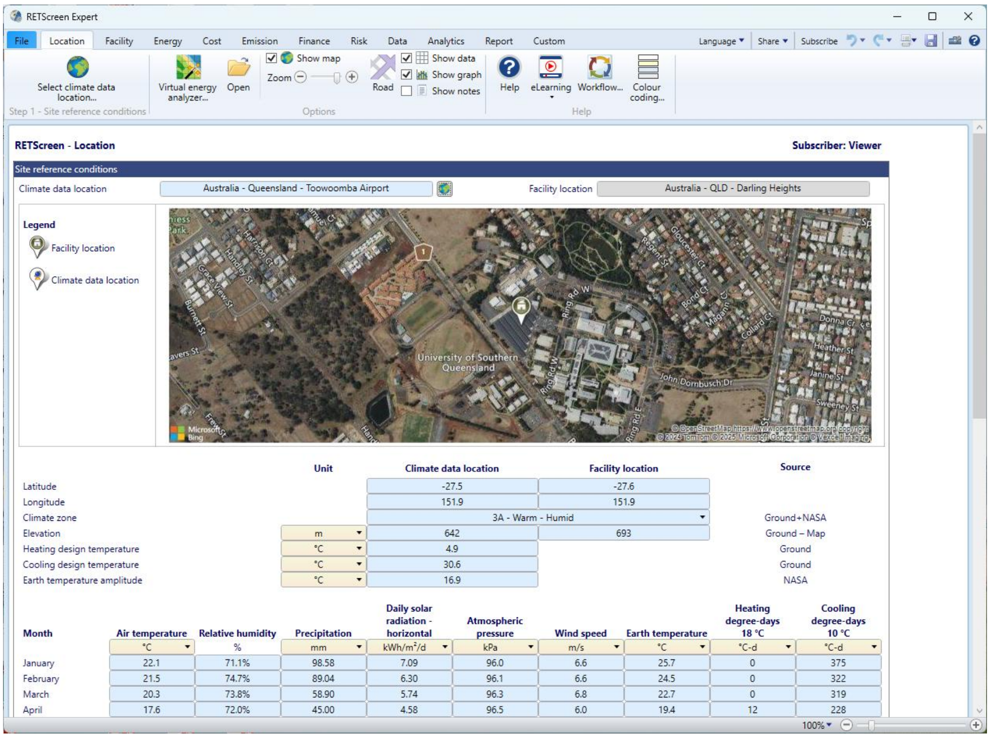
6.3. APPENDIX C: RETScreen

Below are detailed instructions on how to use the RETScreen software. Screenshots of the software follow written step-by-step instructions. No captions are connected to the screenshots since they are embedded in the instructions.

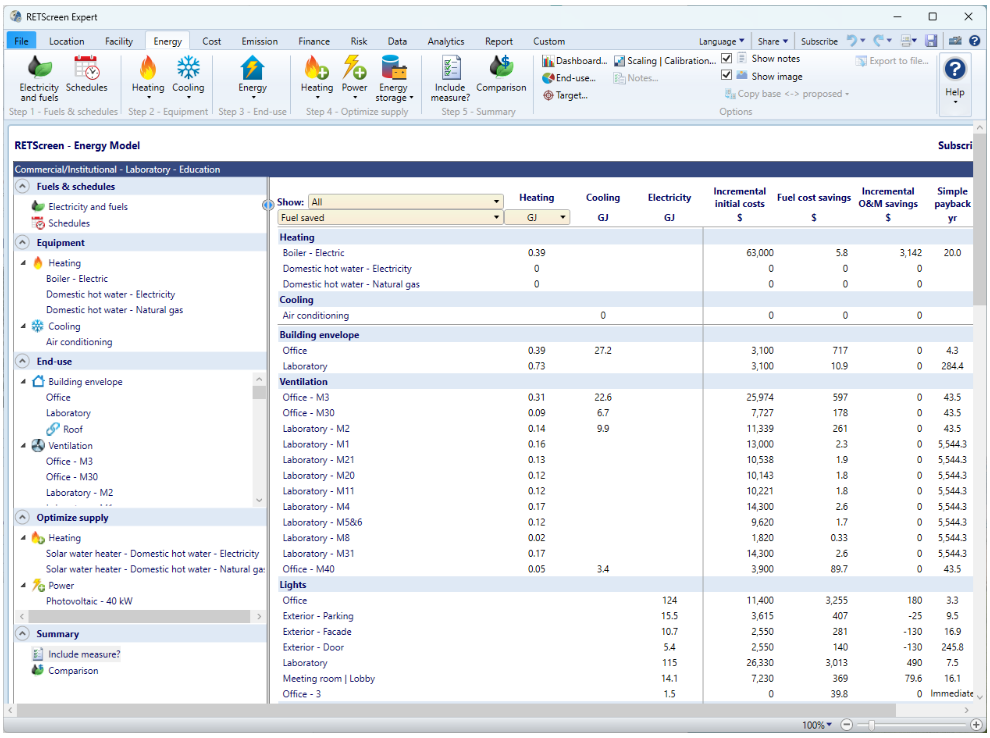
To start the analysis, fill in the fields from the tabs:

1. Location: input the location and type of facility, this will search database to find climate data. Input the Jinko PV system from their database.
2. Facility: this tab lets you specify the type of buildings, commercial or residential
3. Energy: A lot of the energy inputs are unable to be used such as the end use of the electricity, such as heating/cooling and lighting in offices/labs/exterior. I don't have any of that information. The only part of this tab is to input the photovoltaic information. Select the level 2 options and use the search engine to find the Jinko solar panels and the Sunny-Power 60 inverter. To make it comparable to HOMER, use the average output for each month from our data as the load.
4. Cost: this is a simple tab that lets you manually put in the total financial costs.

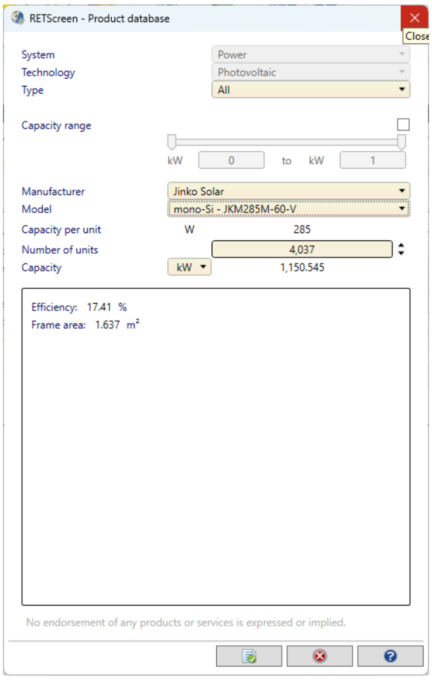
First enter the location and click on the search button, a map will open where you can pinpoint the actual location.



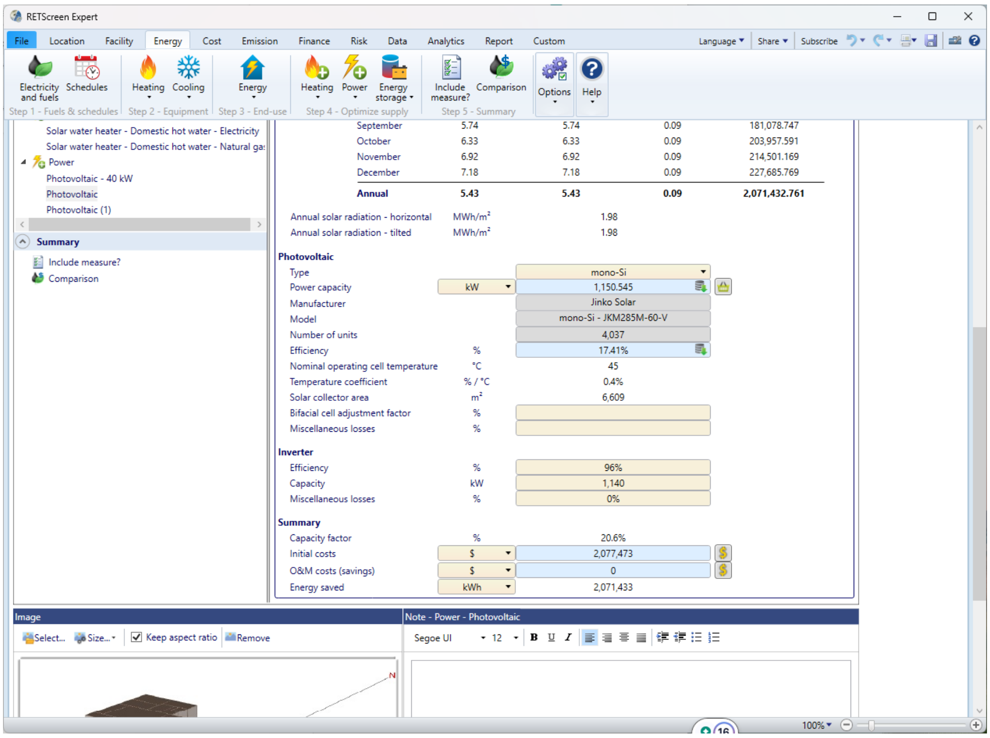
The energy tab has a lot of information about the end use of the electricity which is unknown



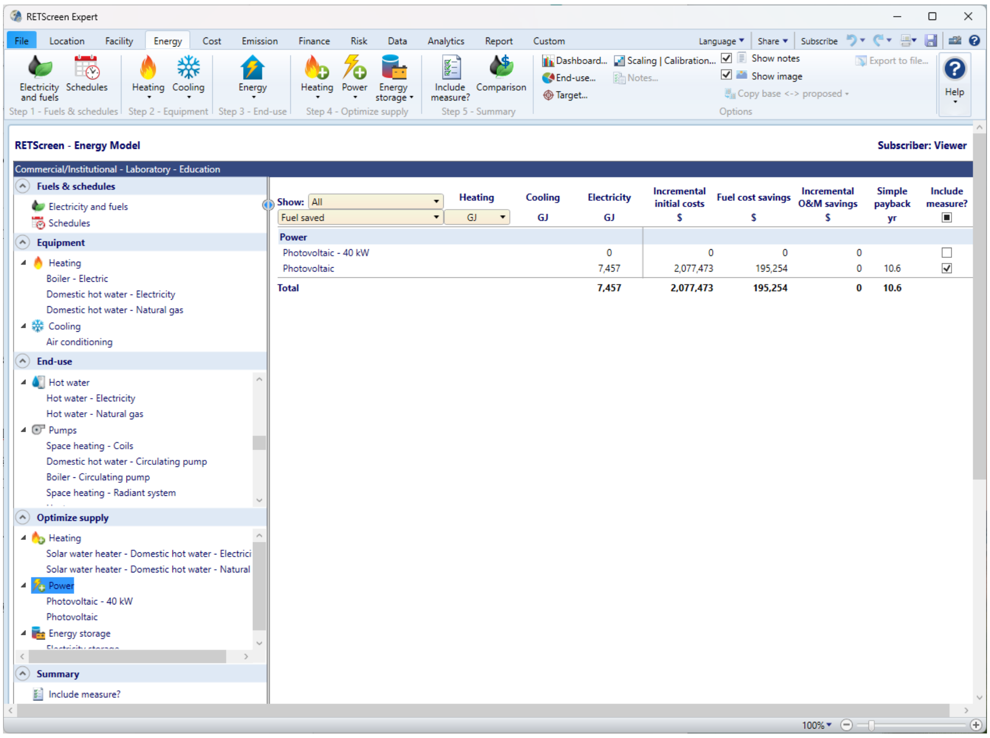
Click on photovoltaic energy and use the database to select Jinko PV system and input the number of panels



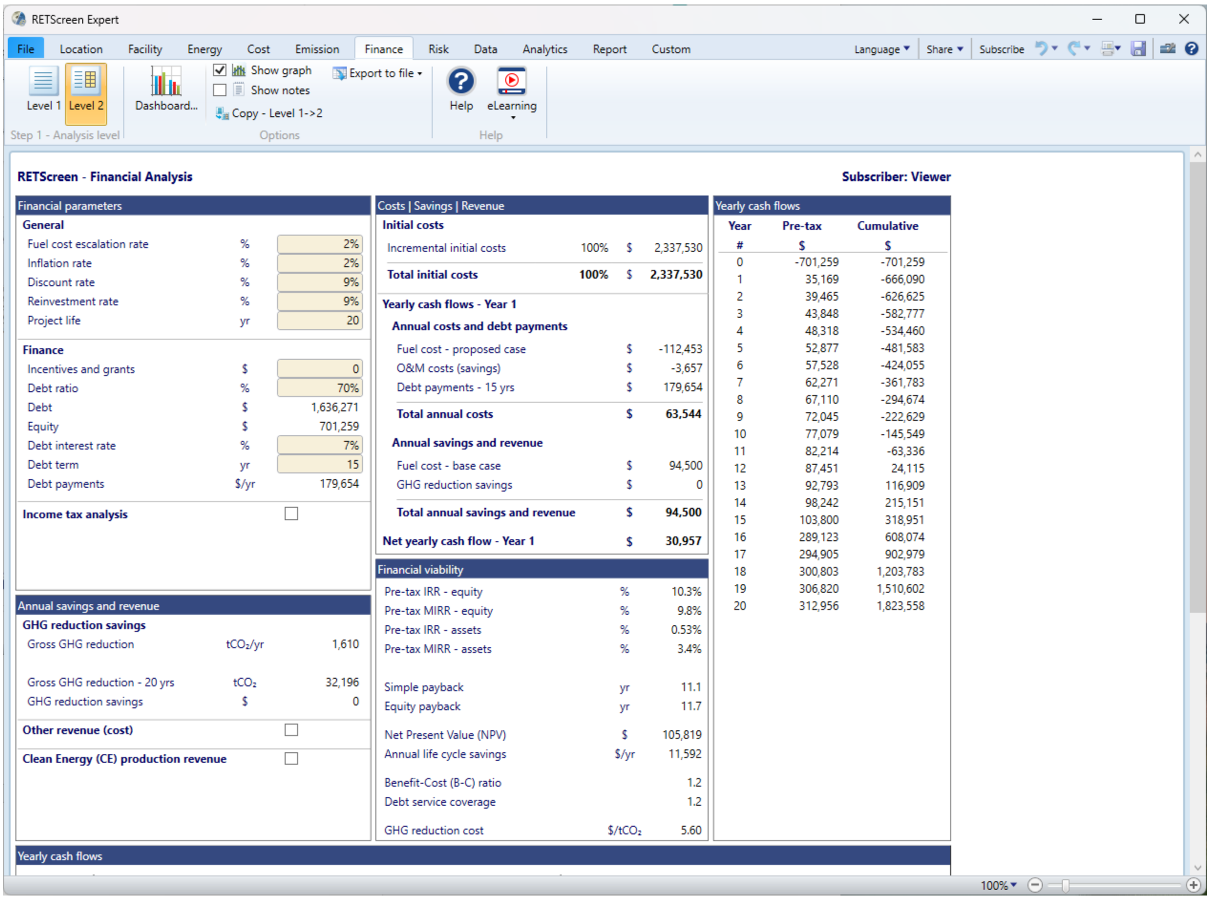
1702 Fill in the inverter information manually based on the known specifications



1703 Simple Payback summary



1704 Financial analysis



1705

6.4. APPENDIX D: PC3D

For this package, there are no databases, so each value needs to be manually entered. The PC3D website outlines a series of examples, one of which is a mono-crystalline PERC. This example can be used to fill in each of the values. The cells that contain a small red triangle contain information about that parameter.

It has easy-to-use instructions embedded on each cell that define what each cell is. Doesn't calculate any financial information, no payback. The information we have from Jinko Holdings contains size and weight parameters for a mono-crystalline PERC and power, voltage, and current specifications. These allow calculations for simulated energy output. There are spreadsheets for recombination and illumination, which cannot be used since we don't have information on those.