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Analysis of Pricing Trends and Grid Parity of Photovoltaic Systems

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SUMMARY

As an alternative, cleaner energy source, solar power is becoming a much bigger player in how electricity is generated and consumed. To assess how economically-viable solar power is in comparison to other forms of electricity, factors such as the return on investment (ROI) can be calculated. In addition, based on the average lifetime of an average photovoltaic (PV) system, energy purchase reduction, and revenue that can be generated by selling excess electricity back to the power grid, the economic viability of solar energy can be determined. The capital and commissioning cost of a PV system will continue to be a major factor in how viable a PV system will be. Thus, observing the trend in PV system costs over the past years will yield a point of grid parity, when solar becomes competitive with existing forms of energy generation, and show the most beneficial time frame for the customer to install the PV system. This paper seeks to provide some insight on how economic using solar energy can be.

KEYWORDS

Solar Forecasting, Photovoltaic (PV) System Cost, Solar Energy Economics.

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1. INTRODUCTION

To determine the economic viability of solar energy, the return on investment (ROI) ratio is used as the primary metric. The ROI time is defined as a ratio between net profit and the cost associated with the initial investment. The higher the ROI ratio on a PV system is in comparison to another power generation system, the more viable that the PV system is in comparison to the other. Prices and costs will be calculated using the normal manufacturer suggested retail price (MSRP) of each module and prices and revenue from a local energy provider, as an example.

In order to analyze the possible effect of a PV system on a normal household, its output must first be analyzed. Due to the changing weather patterns and climate differences between years, any future year will be different from past years. Because of these changes, attempting to forecast the output of a PV system is directly tied to forecasting the weather, since clouds may obstruct the sunlight a PV module sees. To accurately forecast future solar generation, a neural network will be used to provide an estimate of the energy that can be generated by the PV system. The neural network will take in the solar zenith angle and the date-time as inputs and generate an output in the form of the expected global horizontal irradiance (GHI). Using the calculated GHI and efficiency of the chosen solar panels, the expected energy produced can be calculated.

To help attempt maximize the savings provided by the PV system, the effect of adding a battery into a PV system will be observed. The battery would be used to store excess energy generated by the PV system that is not going to be used immediately. As shown in Figure 1 during midday, excess energy produced by a normal PV grid-tied system will be unused when the load at that given moment is already met, since the demand is not high enough to meet the supply.

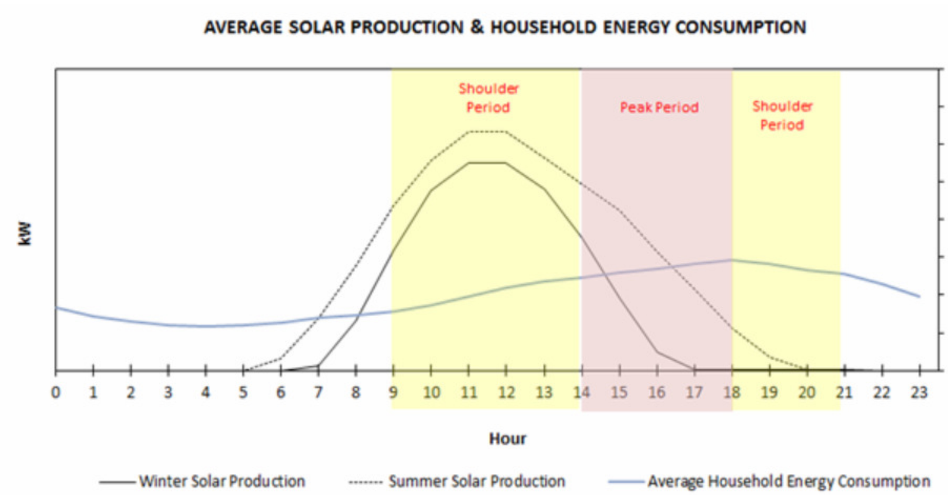

Figure 1: Load vs. Generation Comparison Over Time, Xcel Energy Time of Use Plan [1].

To prevent energy overgeneration, the energy will be stored inside a battery, which will stabilize and redistribute the energy supplied throughout the day. This keeps energy that would normally be unused during the day to be supplied during hours where the PV system would not normally supply enough energy to meet demand (during nighttime hours and hours with low light). Including a battery also keeps the fluctuations of the energy generated by the PV system from affecting the output, since the battery will be able to generate a stable current as long as it is sufficiently charged [2]. This paper will consider the battery to check for any changes in the economic viability of the overall system and whether or not it should be included.

Another method to improve ROI and prevent energy wastage is to sell back excess energy that cannot be currently used back to the grid at a price or incentive determined by the local utility. Depending on the energy provider, the customer could be directly compensated for the energy that they provide to the grid, receive credits that would count towards future energy usage, or other means of compensation. This paper will consider converting the compensation method into a dollar amount, which will be used in the calculation of the ROI. While this method has a direct benefit for the customer, it also has a benefit towards the utility. The customer will no longer be contributing towards the utility's load, rather helping to alleviate it instead. Overall, both the energy provider and the customer would benefit from selling excess energy back.

2. ROI CALCULATION

The ROI ratio is defined as a yearly cash flow in relation to the initial investment over the lifetime of the project. The formula for calculating ROI [3] is defined as follows:

$$ROI = \frac{\sum_{i=0}^{R_{proj}}(C_{i,ref} - C_i)}{R_{proj}(C_{cap} - C_{cap,ref})} \qquad (1)$$

where $C_{i,ref}$ is the nominal annual cash flow for the reference system, C_i is the annual cash flow for the current system, R_{proj} is the project lifetime, C_{cap} is the capital cost of the current system, and $C_{cap,ref}$ is the capital cost of the reference system. In terms of a PV system, the reference system is taken to be a traditional grid-only connection.

3. NEURAL NETWORK SOLAR FORECASTING

To get a tangible amount for energy production, the GHI for a given day must be known in order to calculate the energy produced by the PV system. A closed-loop nonlinear autoregressive with external input (NARX) neural network, shown in Figure 2, is created and trained using weather data [4,5]. To prevent overfitting the data and minimize training time, the neural network uses a single hidden layer containing 25 neurons. The data is preprocessed and fed into the neural network, which outputs data that must be post processed into the GHI value.

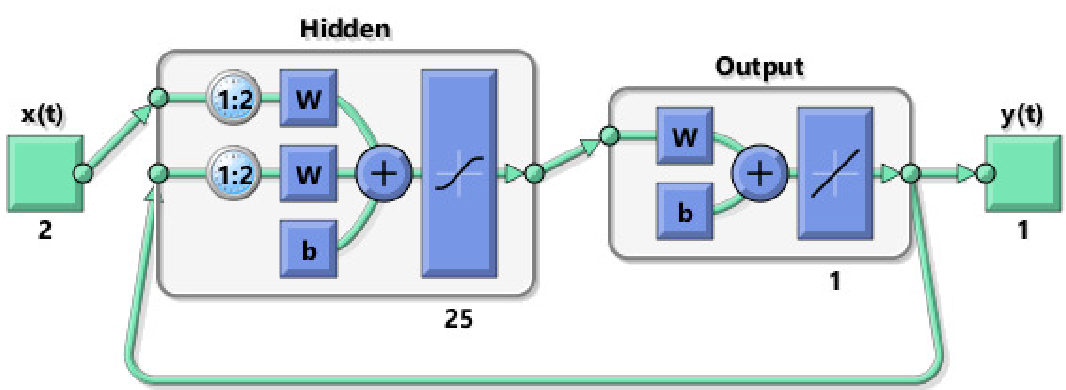

Figure 2: MATLAB Neural Network Diagram.

To train the neural network, the target data must be preprocessed by removing any entries that occur during the nighttime hours where GHI is 0 and normalizing the target GHI values. The GHI values are normalized [4,5] according to the following equations and given to the neural network:

$$normalizedGHI = \frac{daylightClearskyGHI - daylightGHI}{daylightClearskyGHI} \quad (2)$$

The neural network uses the given training target data to configure weights and biases to best match the target data, which is then tested and adjusted using the validation set. Once the neural network is trained and yields an adequate R value, it is then given the test set to evaluate the accuracy of the neural network.

The neural network then outputs a normalized daylight GHI value that must be post processed to yield the actual GHI value. To post process the data, the night time values, set to 0, are added back and the array is denormalized by solving for *daylightGHI* in Equation 2.

When predicting the output for future years, the *daylightClearskyGHI* is unknown. However, the clear sky GHI values can be predicted using the Adnot-Bourges-Campana-Gicquel model [6] as defined in Equation 3. Using the predictive clear sky GHI to denormalize the neural network output, the actual GHI can be found. In Equation 3, G_c is the clear sky GHI in Wm^{-2}, a and b are the regression parameters, and θ_z is the zenith angle.

$$G_c = a(cos\theta_z)^b, a = 951.39, b = 1.15 \quad (3)$$

4. NEURAL NETWORK RESULTS

In this paper, the neural network was created as mentioned above and trained using data from 2003 to 2015 with a 30-minute resolution. The zenith angle was input directly, while the date-time was formatted in Excel as a numerical value. Data from 2016 is used to test the trained neural network, shown in Figure 3. The neural network performs with a mean square error of .0786. The errors can be attributed to the fact that weather is unpredictable over the long term and cloud cover that can cause a drop in GHI. The data from the neural network is then input into HOMER Pro [3] to predict the amount of power that can be obtained from the PV module.

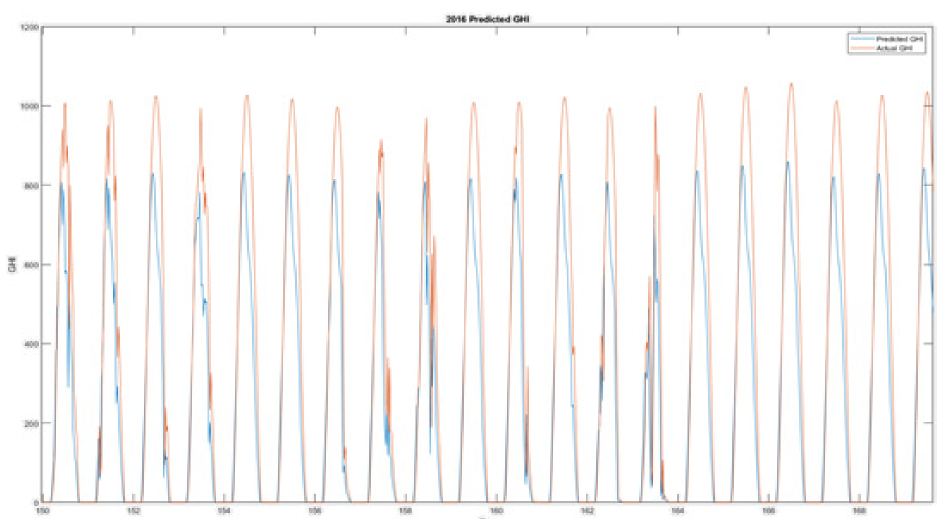

Figure 3: Measured GHI vs. Forecasted GHI (2016).

5. BATTERY ENERGY STORAGE IN A PV SYSTEM

This paper considers two main types of batteries, Lithium Ion and Lead Acid batteries as a means to store energy. Lithium ion batteries have a wide set of benefits over lead acid batteries, such as requiring little maintenance, more options for installation, non-toxic elements, and much higher efficiency. However, Lithium ion batteries are a much more expensive and newer technology than lead acid, which has been used in traditional PV systems for decades. The lowering cost of Lithium ion batteries will increase ROI times if used in the short term but may eventually surpass lead acid in terms of price per performance in the near future as prices drop [7]. This paper highly weighs the effect of the battery on the ROI time, but other factors such as efficiency, lifetime, and overall convenience of the battery will be considered for an average household.

Using HOMER Pro to simulate a PV system in the present day, the optimization tool preferred to use a PV system without a battery included. The optimization tool by default chooses a configuration based on its Net Present Cost (NPC), which is defined as the costs incurred minus the revenue occurred over the lifetime. This result can be explained by the present high costs of batteries. As battery prices continue to decrease, it is possible that battery integrated PV systems will enter the mainstream for residential use as cheaper batteries will be able to store the PV system generation during the day to distribute during times of low generation.

6. SELLING ENERGY BACK TO THE GRID

For the purposes of this paper, net metering is applied as well as assuming a “Time of Use” price plan [1], as shown in Figure 4 and Figure 1, or a standard flat rate plan. A standard “Time of Use” plan works by charging a high rate during demand hours and their lowest rate during off peak hours, with a medium rate during the shoulder hours. The demand hours and first set of shoulder hours coincides with the output hours of the PV system, which is why this is the optimal plan under consideration. In theory, the PV system would output the needed power during the daylight hours and the customer would be able to buy cheaper electricity when possible. This paper will consider 2 different scenarios: storing excess energy in a virtual bank for use later, which is offered by Xcel Energy, and selling back at the current market price of electricity. In the first case, Xcel Energy allows the user to keep track of excess energy that would otherwise go unused and store it in a virtual bank that can be used when generation goes under load, much like a battery would behave. Since there is no physical battery, the energy would come from the grid at no cost to the customer, assuming that they have the virtual stored energy to trade for actual energy. However, other utilities may offer to buy back electricity at the market price at the time of generation. This paper will consider both Xcel Energy’s policy in Colorado, as well as the more general case with a standard purchase/sellback rate.

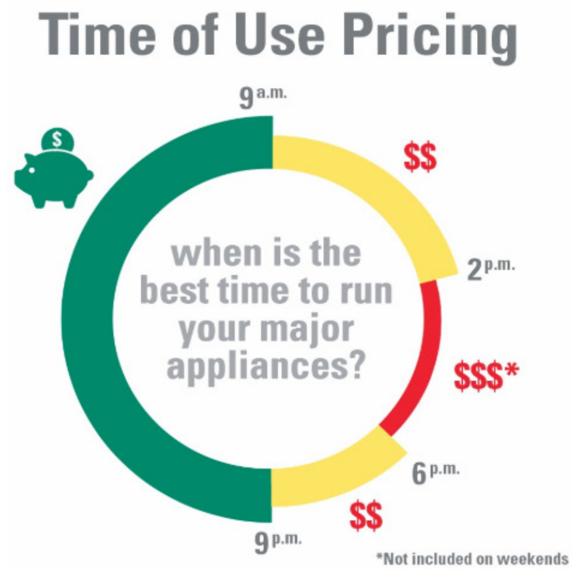

Figure 4: Xcel Energy's "Time of Use" Pricing Plan [1].

7. PRICE TREND OF BATTERIES AND PV SYSTEMS

The price of batteries varies greatly depending on a customer's chosen type of battery. As a relatively new technology, lithium ion is a much pricier option that boasts greater capacity per area, higher usable capacity, and longer lifespan among other benefits. As a long-standing technology, lead acid has started to stabilize in terms of pricing whereas lithium ion has a much higher headroom as research into the lithium ion technology leads to breakthroughs that will reduce its cost. Lithium ion batteries come in two different types: Lithium Cobalt Oxide (LCO) and Lithium Iron Phosphate (LFP). LFP batteries are much more stable than LCO batteries, more resistant to extreme temperatures, and have a longer lifespan. Since LFP batteries are more stable, their installation costs and transportation costs are cheaper, especially when compared to lead acid batteries.

Investigating the battery price trend reveals that since 2010, the average price of lithium ion batteries has decreased at a weighted average rate of about 11.43% from previous years [8]. The average is weighted by year, with closer years having a higher weight than farther years. Forecasting the price trend leads a change in $/kWh as described in Figure 5. The results suggest that by 2025, the price of Lithium Ion batteries will fall under $100/kWh. As of 2018, battery prices are currently around $210/kWh, which falls in line with the forecasted pricing.

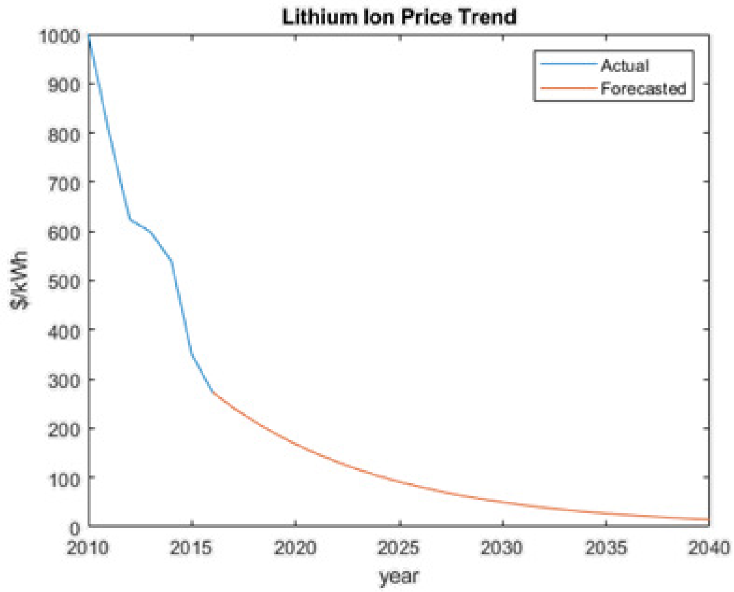

Figure 5: Price Trend of Lithium Ion Batteries.

Moving on, PV modules have also been dropping in prices recently as research leads to many different styles of production for each PV cell within the modules. For observing the price trend, the levelized cost of energy (LCOE) is used as a means to compare the cost of energy produced by PV systems to other types of energy production. The LCOE data is taken from NREL's database based on Kansas City, MO from 2010 to 2017 adjusted for inflation [9]. The data is plotted along with a forecast and NREL's goals for 2020 and 2030. The data is fitted and plotted using MATLAB using a rational fitting equation as shown in Figure 6. The graph shows that the price of PV systems has nearly stabilized, meaning that around the mid-2020, customers will be able to buy into PV systems without having to worry much about wasting their money compared to buying it at a later point.

However, different types of PV modules will differ from the forecasted price due to inherent price differences in production of each type of solar cell. Polycrystalline is currently cheaper to produce but yields a lower efficiency and thus would be on the lower end of the price spectrum than monocrystalline would be. As this paper focuses on the residential case, polycrystalline modules are the choice that would best fit this case due to having enough efficiency to power a house with an adequate amount of area used.

Grid parity is the event in which a form of energy becomes cheap enough to be competitive with existing traditional forms of energy production. Thus, predicting the grid parity of solar is an important aspect of deciding whether or not it can be a viable option for the present [10,11]. Based on the price trend of the PV systems as well as the stabilized price in traditional forms of energy, the graph suggests that grid parity should happen in 2025, as the price trend predicts solar energy to reach $83.7 per MWh. Assuming that coal (with 30% carbon capture and storage) prices stay near $84 per MWh, then solar will become competitive with coal by that year [11]. At that point in time, solar will no longer have to rely on various subsidies to stay competitive with existing forms of energy. As such, a customer would be able to invest in a PV system after 2025 while still paying a similar energy bill. However, depending on their state's incentive and subsidies on solar energy, a customer would still be able to invest in a PV system much earlier.

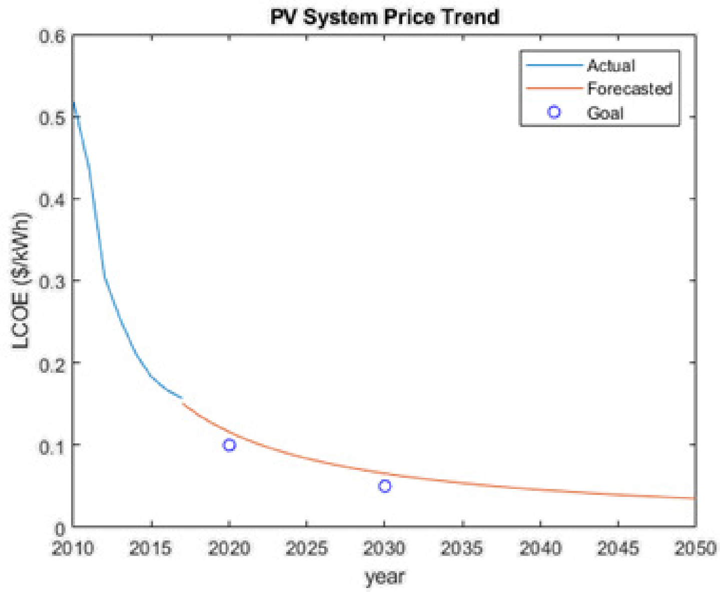

Figure 6: Price Trend of PV Systems.

8. HOMER PRO SIMULATIONS AND ANALYSIS

Currently, HOMER Pro recommends using a polycrystalline PV module without a battery for a residential system. Polycrystalline PV modules sacrifice efficiency for a reduction in price over monocrystalline modules. However, the polycrystalline modules are cheap enough and can output enough energy for the average consumer to supplement their electricity usage easily. On the other hand, battery prices are currently too high for HOMER Pro to suggest using, since batteries can easily cost more than what the average consumer is willing to pay, not including the additional cost towards equipment such as charge regulators which will drive up the cost. As such, even when a battery is forced into a simulation, HOMER Pro will keep the battery at full charge without discharging it since the price per cycle exceeds the price that a customer would buy from the grid. Each configuration has a HOMER Pro default $300 converter, a cycle charging controller, and is set in reference to a normal grid connected house.

Using HOMER Pro's default library with Xcel's plan, the recommended system consisted of a 275 W module, costing around $250, in an array up to around 2.84 kW for a total of about $2,800 total over a 25-year project span. HOMER Pro recommends this specific setup because the optimizer realizes that in Xcel's Time of Use plan coupled with the virtual battery, energy that would normally go to waste during the daytime could be stored in the virtual battery bank for use during times of little to no generation. During on peak hours, the PV module would be much cheaper in terms of price per kWh than importing energy from the grid, thus saving the customer from buying at the highest rate and leaving them to only need to buy during off generation hours when the price is at its lowest. This can also serve to lessen the load on the utility side, since the customer is not consuming energy during the demand period. Overall, the system has an ROI of 10.6%, a simple payback time of 6.73 years, and a LCOE of $0.0611. Considering the average PV module lifetime of 25 years, HOMER Pro implies that the initial investment can be made back within about a quarter the lifetime of the PV system.

Considering a standard plan based on the average price of electricity at around $0.12 per kWh, the preferred configuration is different in terms of scale. HOMER Pro recommends a much larger array at around 12 kW capacity. However, this comes with a much larger initial investment at around $10,000. The economics as measured by HOMER Pro for this configuration is similar from the previous case. For this system, the ROI is 10.1% with a simple payback of 6.83 years and a LCOE of $-0.01988. Overall, the system acts as a net producer, selling about seven times the energy than it imports from the grid. However, as net metering is not available in every state, this is limited to states that offer net metering and selling back to the grid at market price. A higher upfront capital cost may also deter many from using this configuration, since a high capacity PV system must be used in order to capitalize on the ability to generate an income from the system. State dependent laws regarding tariffs may also affect the results an individual customer may get using this configuration.

As shown in the two different cases, both are similar in terms of simple payback time and ROI but differ vastly in cost. The standard plan has a much lower LCOE and has the benefit of being able to generate income over its lifetime from selling to the grid than in the Xcel Energy case, but Xcel Energy's virtual bank and Time of Use plan allows the user to effectively use very little paid energy from the grid and allows using stored energy. As shown in Figure 7, Xcel's plan is able to be completely dependent on solar energy due to its ability to store energy for later use, while the standard plan requires energy to be bought during off peak hours due to a lack of storage. Each simulation uses the same load, but Xcel can supplement its production using the virtual battery (not shown).

For these optimal systems as output by HOMER Pro, changing the pricing on batteries did not result in HOMER Pro including the batteries as the most optimal solution. However, cases where it did include the battery actually did discharge the battery to provide supplementary power, but these cases never surpassed the PV module only configuration as the most optimal. In the Xcel Energy focused simulation, the virtual battery has no additional cost or lifetime associated with it, meaning that a PV user using a pricing plan and net metering policy similar to Xcel Energy's will be able to reap the benefits of having a battery without having to deal with the consequences of replacement, maintenance, or any other hassle since the battery is purely virtual. However, the system will still be grid-tied and will still have the consequences that are associated with a grid-tied system. As solar energy starts to reach grid parity, concepts such as selling energy back to the grid at market price and having a method of rolling over energy, such as Xcel Energy's virtual battery, may be changed to reflect the competitiveness of solar energy.

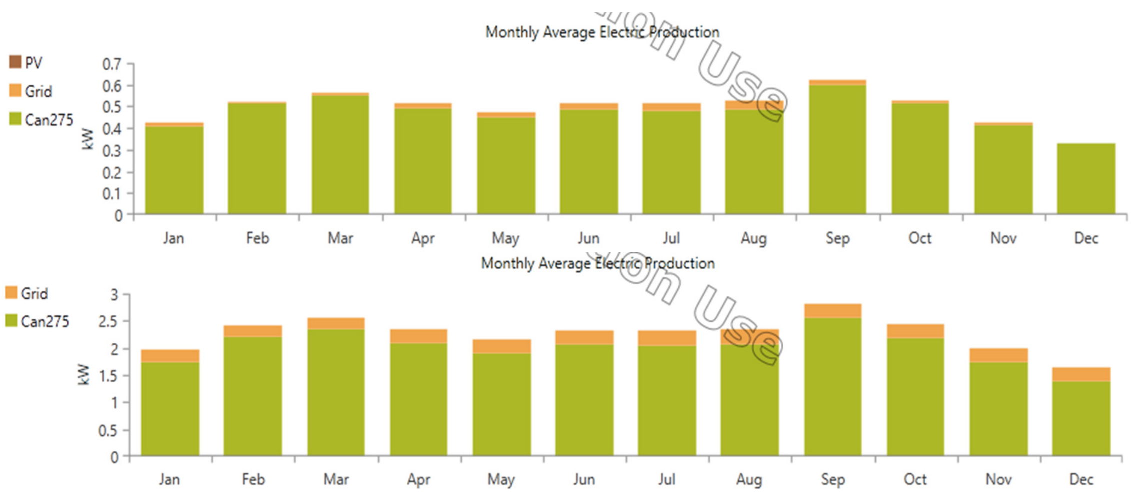

Figure 7: Xcel Plan (top) & Standard Plan (bottom) Electrical Production from HOMER Pro.

9. CONCLUSION

Currently as it is, PV is already a viable option for homeowners if they can afford the large upfront cost that comes with PV modules and associated hardware and if they live in a location with large amounts of sunlight. As this paper considers data local to Denver, Colorado, USA, any prospective customer in Denver would be able to benefit from having a PV only system currently with available subsidies and incentives, as shown by current customers who already own a PV system. Using a neural network to predict the GHI of future years allows for a glimpse at what future power generation can look like and further show how much power would be needed and how much can be saved or sold. Using this information in HOMER Pro allows simulating an average household over the entire year, which provides a detailed economic analysis as well as optimization for the system. The price trend can then be used to predict the prices in both batteries and PV modules to show when grid parity might occur or when a customer would benefit most from a PV system.

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