ME597 Artificial Intelligence in Thermal Systems

Final Report

Title: Development of Solar Farm Specifications for Academic Buildings using Artificial Intelligence

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Abstract

This paper aims to calculate the number of panels it would need to power a building at Purdue University while considering complex variables like weather. A model to predict the power consumption of a building and a model to predict power production of a solar panel were made to achieve this goal. In order to account for the complex variables that affect power production and consumption, a regression artificial neural network was created. Through the models it was found that to satisfy the 25% of Purdue's computer science building's yearly energy needs, 336 panels would be needs. Similarly, to satisfy 50% and 75% of the yearly energy needs, 503 and 704 panels would be needed respectively. The max panels needed to run the building would be 2270 panels and that the months of max power consumption by the building was January, February and March. It was also found that the panels overproduce solar energy on many days and selling this energy back to the grid could serve as a source of income. These results show that fully powering building's on Purdue's campus is an achievable goal and will go a long way in reducing the dependence on fossil fuels

Keywords

Artificial Neural Network, Electric Power Consumption, Machine Learning, Solar Energy, Data science

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1. Introduction

With pollution and global warming become more detrimental to our daily life, renewable energy sources like solar energy might be the solution to stopping the damage that global warming will cause. This project deals with analyzing the possibility of adding solar power as a electricity source for the Lawson Computer Science Building (LWSN) at Purdue University's West Lafayette (WL) Campus.

Solar energy is a renewable power source that uses photovoltaic cells to convert solar radiation to electricity using the photovoltaic effect. This method of producing energy is highly effective in areas that receive a high amount of sunlight.

This project aims to:

- Predict the electric power consumed by a building over a day, given certain details about the building and the weather conditions for that day.
- Predict the power produced by a Photovoltaic (PV) cell in a day, given the weather conditions of the day.
- Calculate the number of PV cells that would be required to meet the daily electric power consumption for the LWSN building, for a percent of days in the year.

This project approached the problem as a data science problem. University building electric power consumption, PV cell electric power production and weather data was collected from multiple sources to train Artificial Neural Networks, which were used to predict values for LWSN under West Lafayette weather conditions.

Since West Lafayette is a city where winters months can lead to long overcast days, it is imperative that the efficiency of the panels be forecasted to ensure that the needs of the building can be met. The models generated by this project could help inform the students as well as staff regarding the viability of such a plan, which will help initiate a discussion regarding the costs and benefits of the transition to solar power.

Additionally, the model used to help predict power savings in Purdue University buildings can be used to create similar predictions for other universities. In this manner, institutions can use this model to create an estimate of the possible benefits for such a transition before more university-centric analysis projects are approved.

2. Literature survey

2.1 Novelty

The basic idea of modelling a solar panel for its power output has been performed before. The salient feature of this project is the fact that it will be Purdue centric and will have a focus on the weather conditions of the Purdue West Lafayette campus, which is something that has not been done. The final aim of the project is to see if whether a Purdue building can be fully converted to solar energy via artificial intelligence models. While the analysis of the viability of solar panels and their cost have been done before and are common calculations people do when they consider buying solar panels, the method of using a Neural Network is what sets this project apart.

2.2 Relevant Papers

2.2.1 Artificial Neural Networks to Predict the Power Output of a PV Panel

This paper was written by Valerio Lo Brano, Giuseppina Ciulla, Mariavittoria Di Falco from DEIM Università degli studi di Palermo in Palermo, Italy. The paper focus on using various types of neural networks to predict the power output of two different types of solar panels in Palermo. This relates very closely to the to the first part of the chosen project, which requires the creation of a model which can predict the power output of a solar panel based off ambient weather conditions. The researchers collected data by using two solar panels, the Sanyo HIT240HDE4 and the Kyocera KC175GH-2 and then used parameters like air temperature, cell temperature and solar irradiance to predict the power output using three types of neural network, the first one was a one hidden layer Multilayered Perceptron, the second was a Radial Neural Network and the last was a gamma memory processing element. The papers key finding was that simpler ANN's generally required longer training time while more complex ANNs needed shorter training time. Results also showed that adaptive techniques can predict the power output of a solar panel with great accuracy and short computational time. This paper can serve as a useful guide due to the similarity of the projects in their objective. The parameter chosen by the research can inspire some of the choices the team might make. The process followed by the researchers in cleaning the data was also very similar to what the team had planned and will serve as a useful resource there. The dataset the researchers used could also be useful in training the model if adequate modifications are done.

2.2.2 Predicting solar energy generation through artificial neural networks using weather forecasts for microgrid control

This research paper develops a way to predict power generated by solar panels in a microgrid based on weather forecasts. Microgrids are local energy grids that can be used by individual organizations or groups of organizations as a source of electricity. They are generally implemented to provide cheaper and environment friendly alternatives to the main grid, while acting a redundant power source. In this paper, the microgrid is taken to have to stages of operation: Islanded and Connected. Islanded is when the microgrid produces power by itself and Connected is when the microgrid provides power along with the main grid to provide power. The part of this paper that is of interest for our research topic was their approach in building an artificial neural network to predict generated solar power based on the weather conditions. The model can estimate the actual energy production to a difference of only 0.5 to 0.9%. This artificial neural network model was then used to predict when a solar panel based microgrid can generate enough energy to keep up with power demand. If the prediction model indicates that the weather conditions are favorable on a certain day, companies can save electricity by using the microgrid in Islanded mode. If the model indicates that weather conditions are not favorable, the microgrid can use its backup systems along with the solar panels to meet demand. Companies can benefit from more reliable and efficient usage of their microgrid, while also ensuring their backup systems are only used when needed. The datasets used by the author involves historical weather data from Basque Country. The approach taken by this paper's authors was to use the same weather data to build a prediction model based on sunrise and sunset times to predict accumulated irradiation. After this, the solar energy produced was calculated using Solar Irradiance I with the formula:

$$P_s = \eta S I\left(1 - 0.005(t_0 - 25)\right)$$

where the efficiency η was taken as 17.59% and Surface area of module S is taken as 1.6767 m^2, and t_0 is the observed temperature of the panel. This paper is useful in giving insight on more unique approaches to our research topic. Here, the authors were able to create a highly accurate model for solar power generation without any data regarding real solar panels, due to their ability to simplify the problem to a matter of predicting solar irradiance based on other weather factors.

2.2.3 A review on the prediction of building energy consumption

This paper explores and evaluates different methods in which the power consumption of a building can be calculated. It compares engineering methods, Statistical methods, Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs). The paper compiles information from many research papers and provides the methodology and the effectiveness of that method to predict power consumption of a building, along with the positives and negatives of following that method. For example, while statistical methods like simple regression are simple to use and can run fast, they may not be the most accurate, whereas engineering methods can provide very accurate predictions, however, are very complicated to conduct. This paper is useful to us as it could help us choose a method to predict power consumption of a building. We also gain important knowledge about the important factors that we should consider when predicting a building's power consumption as the paper talks about different papers that used different factors and how accurate each paper was. The paper itself contains no research however it summarizes the findings of many different papers which we could refer to if required. The main finding of the paper is that the power consumption of a building is complicated to predict and while there are many different methods to make the prediction, each method has its own benefits and drawbacks, and can be applied well in different scenarios.

3. Description of the datasets

3.1 Weather Data

The weather data was sourced from the National Solar Radiation Database, which is operated by the National Renewable Energy Laboratory, which provided hourly data regarding the following quantitative variables:

1. **DNI:** Direct Normal Irradiance, the amount of solar radiation received by a unit surface normal to the sun during the 60-minute period.
   Units are Watt-hours per square meter (Wh/m^2)
2. **DHI:** Diffuse Horizontal Irradiance, the amount of solar radiation received by a unit horizontal surface from the sky (excluding the solar disk) during the 60-minute period.
   Units are Watt-hours per square meter (Wh/m^2)
3. **GHI:** Global Horizontal Irradiance, the total amount of shortwave radiation received by a unit horizontal surface during the 60-minute period.
   Units are Watt-hours per square meter (Wh/m^2)
4. **Clearsky DHI:** Estimation of Diffuse Horizontal Irradiance during clear sky conditions.
   Units are Watt-hours per square meter (Wh/m^2)
5. **Clearsky DNI:** Estimation of Direct Normal Irradiance during clear sky conditions.
   Units are Watt-hours per square meter (Wh/m^2)
6. **Clearsky GHI:** Estimation of Global Horizontal Irradiance during clear sky conditions.
   Units are Watt-hours per square meter (Wh/m^2)
7. **Wind Speed:** Wind speed at the time of measurement.
   Units are Meters per second
8. **Precipitable Water:** Estimation of the total precipitable water height for a unit cross-sectional column at the time of measurement
   Units are Centimeters
9. **Wind Direction:** Wind direction at the time of measurement.
   Units are Degrees from North.
10. **Relative Humidity:** Relative humidity at the time of measurement
    Units are Percent
11. **Temperature:** Temperature at the time of measurement
    Units are in Celsius
12. **Pressure:** Atmospheric Pressure at the time of measurement
    Units are in Millibar

The weather data from the NSRDB was taken for the following places:

1. **Berkeley, California:** City where University of California Berkeley is located.
2. **Orlando, Florida:** City where University of Central Florida is located
3. **Amherst, Massachusetts:** City where University of Massachusetts, Amherst is located
4. **West Lafayette, Indiana:** City where Purdue University is located

The hourly weather data was compiled into daily mean values for each datapoint, as well as maximum and minimum values for DNI and Temperature.

3.2 Electric Consumption Data

The electric consumption dataset was created using web requests to power energy dashboards for University of California Berkeley and University of Central Florida, along with other relevant information such as square feet and the type of building. This data was compiled and stored with the weather data in a combined file. The quantitative and qualitative variables are:

1. **Power Consumption:** Power consumed by the university building in the 24-hour period. Units are Kilowatt-Hours (kWh)
2. **Weekday:** Holding a binary value indicating 0 for a Weekday (Monday – Friday) and 1 for a Weekend (Saturday and Sunday).
3. **University Name:** Name of the University for the current set of measurements
4. **Building Name:** Name of the Building for the current set of measurements
5. **Square Feet:** The area of the building, as reported by the university. Units are Square Feet (ft^2)
6. **Type:** Qualitative variable indicating whether the building is mostly used for Classroom related activities, or Laboratory related activities. Where 0 is used for Classroom and 1 is used for Laboratory

3.3 Solar Energy Production Data

The solar energy production data was sourced from University of Massachusetts Amherst's solar energy dashboard. This data was combined with the weather data for Amherst, Massachusetts to train the solar energy production model. The variables for the solar energy production data are:

1. **Power produced:** Power produced by all the PV cells installed at the Computer Science building at University of Massachusetts Amherst over a day. Units are Kilowatt-Hours (kWh)
2. **Number of cells:** Number of PV cells installed at the Computer Science building at University of Massachusetts Amherst.
3. **Power produced per cell:** Power produced by one PV cell installed at the Computer Science building at University of Massachusetts Amherst over a day. Units are Kilowatt-Hours (kWh)

4. Methodology

4.1 Type of Models Chosen

Both the models being created will be predicting a numerical value for power output and power consumed. The model will not be classifying energy consumption or any other parameter, hence, regression makes the most sense in this regard. An ANN was chosen because of the model's adaptability to large number of variables and large amounts of fluctuations in those variables. The ANN will also allow for a large amount of nonlinearity to be present in the model, which will be very useful for unpredictable data like weather data, which has extremely complex scientific phenomenon guiding it and power consumption data which could be heavily dependent on human factors.

4.2 Dataset processing

4.3.1 Weather Data Cleaning

Firstly, the data in the date column was split into its individual components, namely the day, month and year. Secondly, any rows with 0 DNI were dropped as well. The raw data had been measured by the hours and to convert it into daily form, the data was averaged and columns for the max and min of the temperature and DNI were created as well

4.3.2 Electricity Generation cleaning

The data obtained from University of Massachusetts contained power produced by all the photovoltaic cells installed at the Computer Science building. The number of PV cells installed was obtained and used to calculate the power produced by each PV cell at the Computer science building in a day.

4.3.3 Electricity Consumption cleaning

After obtaining data by making web requests, the data first removed any clear outliers of data, that resulted from bad requests. For example, many buildings in the University of Central Florida did not report electricity consumption for the first four months of 2017, these datapoints were removed. Then, a few qualitative variables were added to the data, including whether the current day of the week was a weekday (Monday to Friday) indicated by 0, or a weekend (Saturday and Sunday), indicated by 1.

4.3 Brief description of the model:

1. Solar Energy Prediction

As mentioned in section 4.1, This model will be a regression model that will take in the DHI, DNI max, DNI mean, GHI, clear sky DNI, clear sky DHI, clear sky GHI, wind speed, precipitable water, relative humidity, temperature, max temperature, min temperature and pressure. The model will output the power outputted per panel in kilo Watt hours. The model only has densely connected layers and uses the Rectified Linear Unit as the activation function for the input and hidden layers, while the output layer uses the linear activation function. Each layer also makes use of l1 regularization. It also makes use of call backs like early stopping, reduce learning rate and dropout to improve the loss and combat overfitting. Finally, the model uses the Adam optimizer

2. Building Consumption Prediction

This model is like the previous one in that it is also a regression model and that all the inputs related to weather are the same, however, this model also takes in 2 qualitative inputs, whether or not this power has consumed on a weekend or a weekday and if the building has been used for classrooms or laboratories. This model also uses densely connected layers with the same callbacks and optimizers as the previous model but does not use a regularizer.

Since both the models being made are regression models, the Mean Square Error (MSE) and the Root Mean Squared Error (RMSE) will be used to evaluate model performance.

4.4 Hyperparameter tuning

The hyperparameters that were targeted for tuning are the number of neurons per layer, the number of layers, the initial learning rate, the early stopping and reduce learning rate patience, the value of the l1 regularizer, the reduce learning rate factor and the dropout percentage per layer

5. Results and Discussion (~ 5 pages)

5.1 University Model Results

5.1.1 Comparison with Testing Data

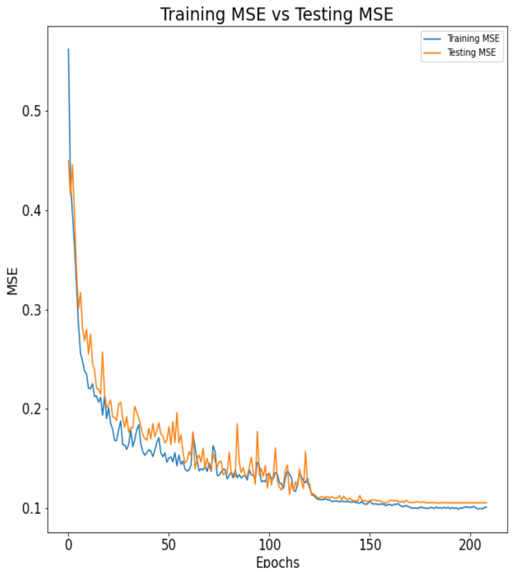


Fig 5.1a Change in loss as number of epochs increases

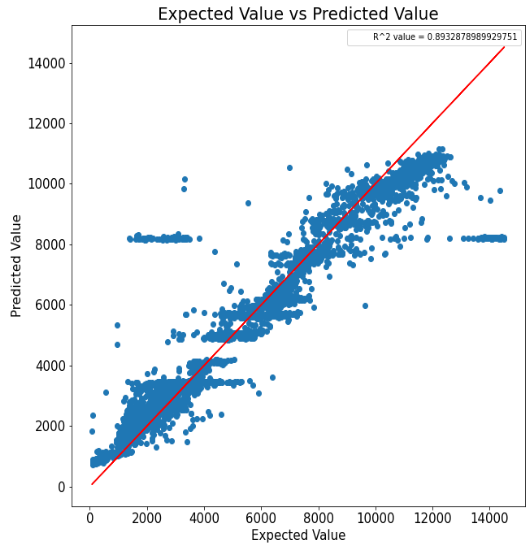


Fig 5.1b Comparison between expected value and predicted value

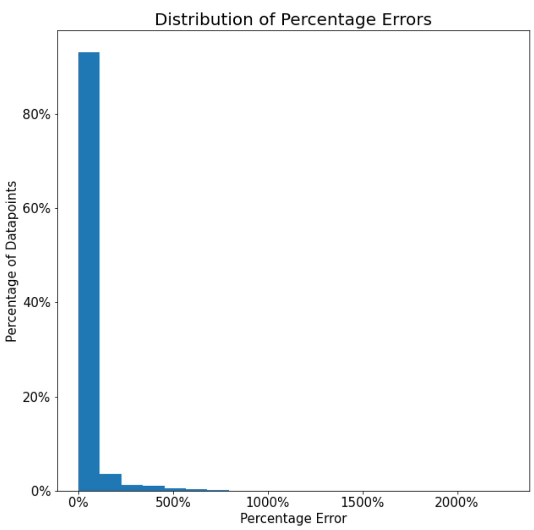


Fig 5.1c Histogram depicting distribution of errors

As visible in *Fig 5.1c*, even though there are notable outliers, most of the data has a small percentage error. There are very few outliers in the model, with most of the data remaining the first bin.

We calculate percentage value as

$$\left|\frac{\text{Predicted Value} - \text{Expected Value}}{\text{Expected Value}}\right| \times 100$$

The r^2 value of the model is 0.89, which is a reasonably high value for the model. An ideal model would have an r^2 value of 1.

5.1.2 Comparison against University of Michigan monthly data

The highest resolution available for University of Michigan electric consumption data was monthly data. Hence, our methodology for comparing monthly data was to use daily weather to predict electric consumption for all 365 days of the year. We then computed the predicted electricity consumption for each month and compared it against the reported monthly data values.

	Result	**Actual**	**Difference**	**Percentage Error**
count	12.000000	12.000000	12.000000	12.000000
mean	231340.203125	250341.083333	19000.888021	11.012780
std	8570.139648	31378.512646	35202.665400	8.729914
min	216333.968750	212259.000000	-29133.265625	0.806130
25%	226105.914062	226137.250000	-3848.199219	2.621449
50%	231138.476562	240094.500000	11807.757812	9.401439
75%	237283.441406	276124.500000	47216.402344	16.918565
max	243082.468750	300123.000000	72113.031250	25.000444

Fig 5.1d Table describing Result (Predicted Value) vs Actual (Reported Value)

As noticed in *Fig 5.1d*, the model's prediction for the monthly electric consumption was able to achieve an estimate with a mean error of 11%. This indicates that the model was able to estimate the electric consumption of a university building that did not belong to the universities which were used to train the model.

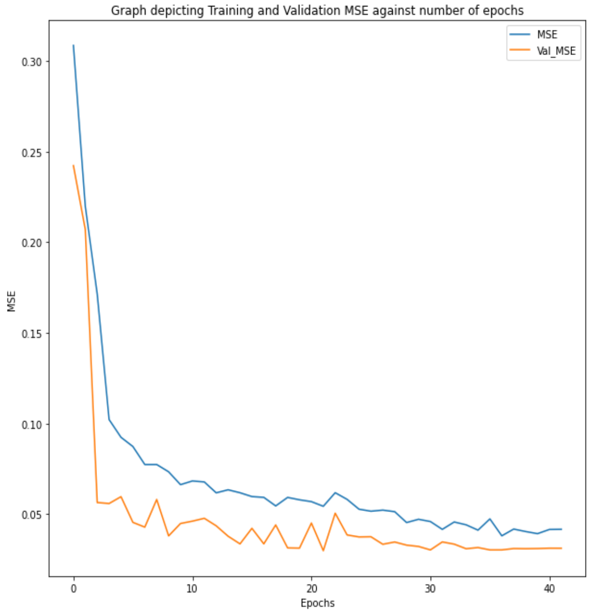
5.1.3 Final Model Specifications

<table>
<tr><th>Hyperparameter</th><th colspan="7">Value of Hyperparameter</th></tr>
<tr><td>Total Epochs</td><td colspan="7">400</td></tr>
<tr><td>Batch Size</td><td colspan="7">90</td></tr>
<tr><td>Number of layers</td><td colspan="7">1 input + 5 hidden + 1 output</td></tr>
<tr><td rowspan="2">Number of Neurons per layer</td><th>Input</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>Output</th></tr>
<tr><td>512</td><td>256</td><td>128</td><td>64</td><td>32</td><td>16</td><td>1</td></tr>
<tr><td>Dropout rate</td><td colspan="7">0.3</td></tr>
<tr><td>Learning rate</td><td colspan="7">0.001</td></tr>
<tr><td>Optimizer</td><td colspan="7">Adam</td></tr>
<tr><td>Early Stopping Patience</td><td colspan="7">50</td></tr>
<tr><td>Reduce Learning Rate Patience</td><td colspan="7">10</td></tr>
<tr><td>Reduce Learning Rate Factor</td><td colspan="7">0.2</td></tr>
</table>

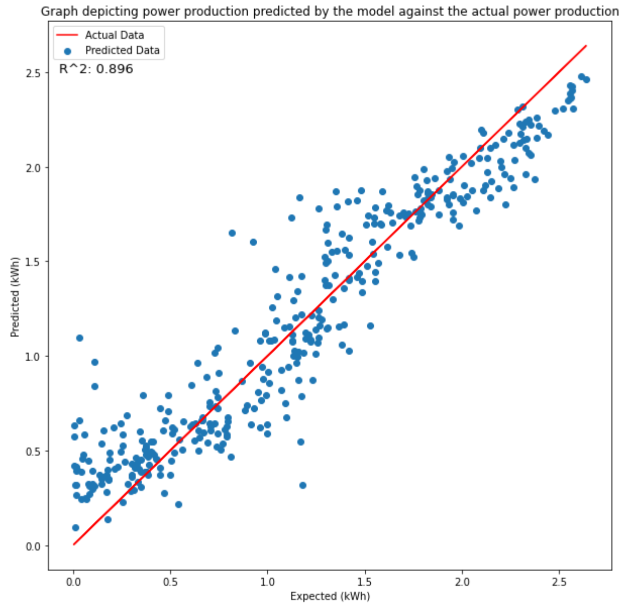
Fig 5.1e Description of Hyperparameters

5.2 Solar Model Results

5.2.1 Final Model Metrics



5.2a Change in loss as the number of epochs increases



5.2b Comparing the predicted results to the expected results

The after training the model had a mean squared error (MSE) of 0.0380 on the training data and a MSE of 0.0334 on the validation data. The model also has an RMSE of 0.1827 and 0.1949 for validation and training respectively. *Fig 5.2a* shows the change in the MSE as the number of epochs increase. At the point where the model stops, the graphs does not show any signs of overfitting just yet, however as the model has early stopping active, it is possible that it could overfit in the next 10 epochs or so. *Fig 5.2b* compares the values that the model has predicted versus the actual values of the validation data. Ideally, the data points should be along the red line, but as seen in the figure, the data follows the general trend but does not follow the line exactly.

5.2.2 Final Model Specifications

<table>
<tr><th>Hyperparameter</th><th>Value of Hyperparameter</th></tr>
<tr><td>Number of layers</td><td>1 input + 5 + 1 output</td></tr>
<tr><td>Number of Neurons per layer</td><td><table><tr><th>Input</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>Output</th></tr><tr><td>512</td><td>256</td><td>128</td><td>64</td><td>32</td><td>16</td><td>1</td></tr></table></td></tr>
<tr><td>Value of l1 regularization</td><td><table><tr><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th></tr><tr><td>3.5e-4</td><td>3.5e-4</td><td>3.5e-4</td><td>3.5e-4</td><td>3.5e-4</td></tr></table></td></tr>
<tr><td>Dropout Per layer</td><td><table><tr><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th></tr><tr><td>0.3</td><td>0.3</td><td>0.3</td><td>0.3</td><td>0.3</td></tr></table></td></tr>
<tr><td>Learning rate</td><td>0.001</td></tr>
<tr><td>Early Stopping Patience</td><td>20</td></tr>
<tr><td>Reduce Learning Rate Patience</td><td>5</td></tr>
<tr><td>Reduce Learning Rate Factor</td><td>0.2</td></tr>
<tr><td>Optimizer</td><td>Adam</td></tr>
<tr><td>Total Epochs</td><td>200</td></tr>
</table>

Fig 5.2c Model Hyperparameters

5.3 Purdue Analysis

5.3.1 PV Cell requirements

Running the model with the Purdue weather data provided the following results:

- The minimum number of solar panels to meet the electricity requirements for just one day is 336 PV cells.
- To meet the electricity requirements for 50% of the days in the year, we would need 503 PV cells.
- To meet electricity consumption requirements 75% of the year, 704 PV cells would be required.
- Finally, 2270 PV cells would be required to surpass the electricity needs of LWSN every day of the year

These results are visualized in *Fig 5.3a*.

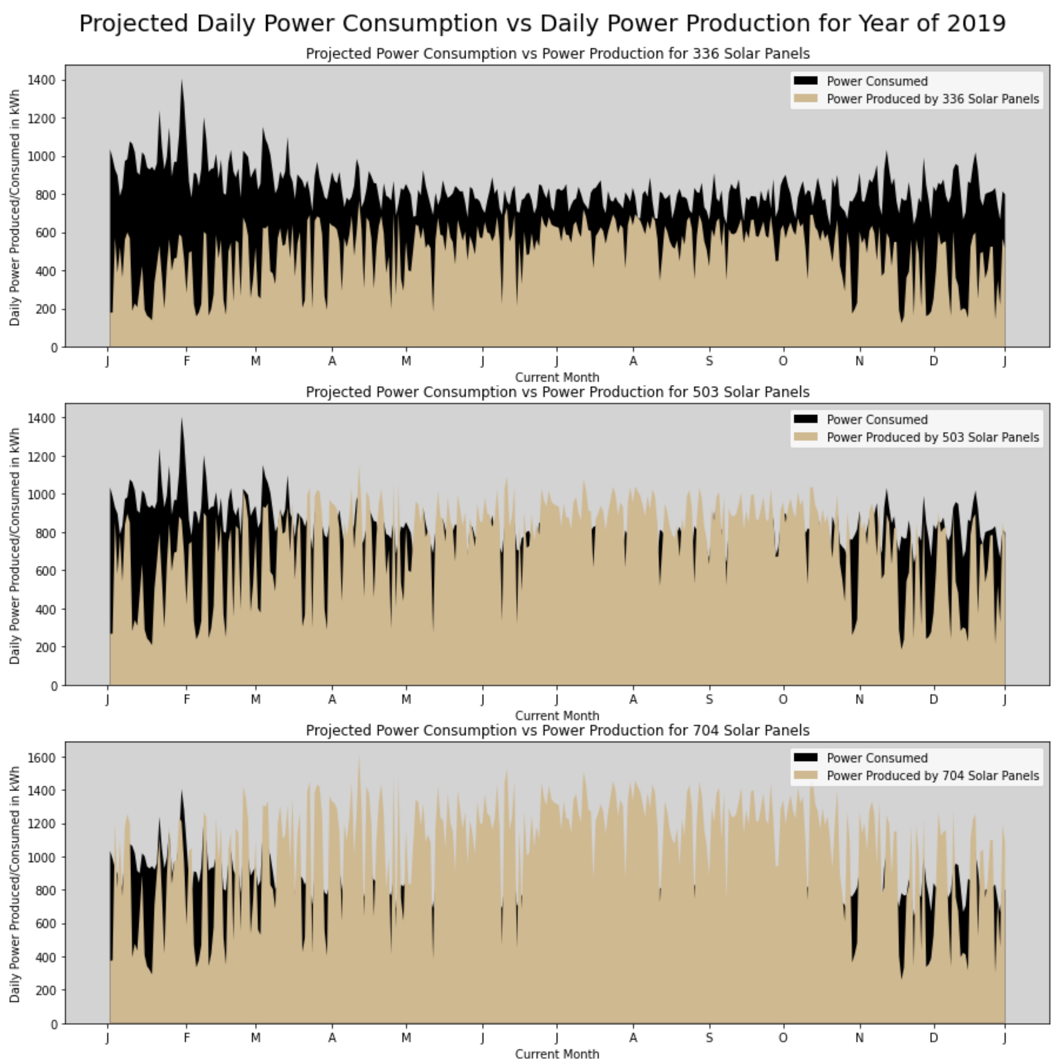


Fig 5.3a Graphs that compare predicted power consumption and predicted power production for a variable number of solar panels

Number of Solar Panels	Projected Electricity bought from Grid (% of total)
336 Solar Panels	39.29%
503 Solar Panels	17.11%
704 Solar Panels	8.9%

Fig 5.3b Projected Electricity bought from Grid (% of total)

5.4 Discussion

In *Fig 5.3a* the exposed black areas are the days on which the predicted electricity consumption exceeded the predicted electricity of the PV cells. While a generalization can be made from these graphs that more PV cells reduce the number of days where energy must be bought from the grid, there are possibly some sources of error in the method that could affect the exact values of PV cells obtained.

- **Building assumptions**: The model assumes that the power draw of the Purdue CS building will be like that of buildings of similar size at University of California Berkeley and University of Central Florida. This may not be the case if the usage of the building is very different however since it is mainly a classroom, that assumption could be made. The model was tested on a building at University of Michigan and produced satisfying results, hence it is assumed that it did the same for Purdue.
- **Insufficient data:** Another cause of errors could be insufficient factors being used to train the models. This was combatted by reading multiple research papers on the topic and using all the factors that these papers deemed important

A higher number of panels results in fewer days where excess grid electricity is required to meet the electricity requirements of LWSN. Hence a high number of PV cells are ideal, however there are other external factors that could affect the number of panels that can be installed:

- **Limited space:** Since PV cells must be installed without being covered in any manner, they can cover a large amount of area, hence the space available could be a bottleneck.
- **Cost:** There is a significant initial cost to installing solar panels as it requires the procurement and installation of a large amount of PV cells and other equipment like inverters etc.
- **Maintenance:** PV cells must be cleaned regularly, hence installing a large amount could lead to significant maintenance challenges which could affect the efficiency of the cells and significant maintenance cost as well.
- **PV cell:** This model predicts the number of PV cells as the same cells that were used at University of Massachusetts, Amherst, however using different PV cells would require the model to be trained for the new PV cell based on existing data and this would change the number of PV cells.

Additionally, this model does make certain simplifications that could factor in when analyzing the cost effectiveness of this setup.

- **Storage of electricity:** The model is created assuming that no electricity can be stored. Excess power produced in a day could be stored and used on days where less energy is produced. For example, if there is a cloudy day where electricity consumption is high, the reserves could be used to meet the power consumptions needs in place of buying electricity from the grid.
- **Selling to the grid:** When looking at the project from a financial perspective, it is also important to consider the fact that excess energy can be sold back to the grid, and this could help finance the project.

6. Conclusion

Hence, a model to predict the electric consumption of a building based on features such as square feet and purpose, along with data about the weather as well as a model to predict the electric power generated by a single photovoltaic cell were created. By predicting electric consumption for the Lawson Computer Science building, as well as estimated electricity production for a model subjected to Purdue weather, an estimation for the number of solar panels required to cover electric consumption of the Lawson Computer Science building was created.

The analysis concludes that 336 Solar Panels would cover 60% of the Lawson building's electricity consumption in a year, while 704 Solar Panels would cover 92% of Lawson's total consumption, also fully powering the building for 274 days out of the 365 days in a year. These numbers help to conclude that there is a viable path to substantially decrease dependence on fossil fuels for electricity in Purdue University.

7. Acknowledgements

I would like to thank Professor Hasti for his guidance during this project. His guidance during the early stages turned out to be invaluable, and helped us proceed in the right direction.

8. References

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