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Predicting Residential Economic Photovoltaic (PV) Potential Using Data Science

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Abstract: *The major objectives of this paper were to apply machine learning algorithms to residential PV renewable energy systems to enable the assessment of its economic potential. In doing so, suitable challenges and pathways towards a sustainable energy transition for Trinidad and Tobago were identified. Data science principles were used to estimate the necessary data required to model residential PV systems. The model, which utilizes the Ridge Regression machine learning algorithm, estimated daily residential electricity consumption based on bi-monthly data available from the utility companies as well as the average daily temperature. It was found to have an accuracy of 69.7% as compared to the average actual daily values.*

Subsequently, the pvlib python library was used to design PV systems of sizes 2kW, 3kW, 4kW, 6kW and 10kW for a random sample of households in Trinidad and Tobago and the demand charge savings possible from these systems were calculated. This model can be used by consumers, power producers and local PV companies to help assess the suitability of a PV system for a particular household in a quick and open-source manner.

To use the model as it presently stands, users must have the knowledge for using Jupyter Lab, an IDE for the python programming language. Additionally, users must have at least two (2) bi-monthly periods of data, from 2018 or sooner, for their household.
Keywords: *Solar PV, machine learning, economic potential, Ridge regression, pvlib.*

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I. INTRODUCTION

Due to the negative impacts of climate change, the world is undergoing an energy transition. This transition is centered around a reduction in the usage of fossil fuels using renewable and zero-carbon energy (IRENA, 2022). Renewable energy technologies such as solar, wind and hydro, alongside carbon capture, geothermal and hydrogen fuel cell technologies, are important tools in the pursuit of this initiative. The transition to an energy economy less dominated by fossil fuels promotes sustainable development which is the basis of modern-day policy making. In keeping with this ethos, the transition must be implemented in such a way that the livelihoods of the most vulnerable members in society are not threatened (Weir, 2015).

As highlighted by the Covid-19 pandemic, electricity reliability and affordability has become a critical aspect of the well-being of people (International Energy Agency (IEA), 2021). It is therefore more important than ever for countries heavily reliant on fossil fuels, such as Trinidad and Tobago, to diversify their energy sector and increase levels of energy security unconstrained by hydrocarbons. That is, for sustainable development, the trend in the rise of electricity (energy) demand requires a parallel increase in renewable energy technologies. Any feasible energy transition requires consideration of the multidirectional nature of energy flows brought about by distributed generation. As fossil fuels still retain the lion's share of global energy production and consumption, they cannot be eliminated in the immediate future. The IEA highlights a 6-phase system for the integration of RE technologies (International Energy Agency (IEA), 2021).

Technological advancements for renewable energy have continued to grow in recent years. Improvements in efficiency as well as a reduction in the cost has been achieved. However, there still exists significant technical barriers to the large-scale adoption of such technologies. One major barrier in T&T is the high initial costs coupled with lack of investors and significant competition from the subsidised fossil fuel electricty generation (Seetharaman, 2019). As such, there is still need to perform data driven analysis in T&T to ascertain a more enabling economic enivronment for renewable energy penetration with respect to subsidy reform and feed-in traiffs/net metering.

The energy mix in Trinidad and Tobago has been largely dominated by oil and gas for many decades. Trinidad and Tobago is the leading producer and exporter of hydrocarbon-based products in the Caribbean. As a result of this abundance of energy dense fossil fuels, Trinidad, and Tobago's economy, as well as its energy generation sector has become heavily reliant on hydrocarbon resources (Manickchand, 2011). Electricity generation in Trinidad and Tobago is provided via a centralized grid of government owned and independent power producers. (Ministry of Energy and Energy Industries , 2022). All power producers, whether government owned or independent, must be licensed by T&TEC (Ramjohn, 2015).

As was demonstrated by the island-wide power outage in early 2022 (Gonzales, 2022), centralized electricity generation has significant drawbacks. This, coupled with the government's goals in the Vision 2030 National Development Strategy, shows the necessity for the encouraged integration of renewable energy technologies (Ministry of Planning and Development , 2016).Renewable Energy is being slowly introduced in Trinidad and Tobago. The Ministry of Energy and Energy Industries has supported this local energy transition through several pilot projects as well as revision of legislation and the national electric code and the pursuit of increased public awareness. The country of Trinidad and Tobago has an extremely low level of energy poverty with 100% of the population having access to electricity. Residential electricity generation locally accounts for 29% or the total electricity consumed. In a 2019 National energy efficiency monitoring report of Trinidad and Tobago, it was noted that monitoring, data gathering, and demographically based analyses would be essential in the integration of renewable and efficient energy source penetration in this sector. As seen in global energy trends, the rate of change in GDP is directly proportional to electricity consumption. This correlation provides a basis for essential analyses required to drive policy decisions for forecasting and transformation of residential electricity generation (Indar, 2019).

It is inevitable that the global energy transition will bring about fundamental technical and societal changes in how electrical systems operate. One of the major barriers to these changes is the potential threat to sustainable development. The viability of renewable energy technologies is no longer primarily limited by technical and physical factors, but by institutional ones (Weir, 2015). However, it must be noted that flexibility and power quality are relevant technical constraints for the integration of intermittent energy sources to the electrical grid (Mamahloko Senatla, 2018). Engineers and policy makers are therefore faced with the charge of ensuring sustainable energy development. This study aims to present a model which may be used by stakeholders, such as power producers and end users, in the future to help make informed decisions about the deployment of renewable energy technologies as it relates to solar energy through the following objectives:

- To utilize data science principles for renewable energy potential assessment.
- To assess the economic potential for PV residential electricity generation in Trinidad and Tobago.
- To identify challenges faced by Trinidad and Tobago in the integration of renewable energy technologies.
- To identify how much demand charge savings can a consumer achieve via the introduction of net metering to PV residential electricity generation in Trinidad and Tobago

II. EXPERIMENTAL PROCEDURE

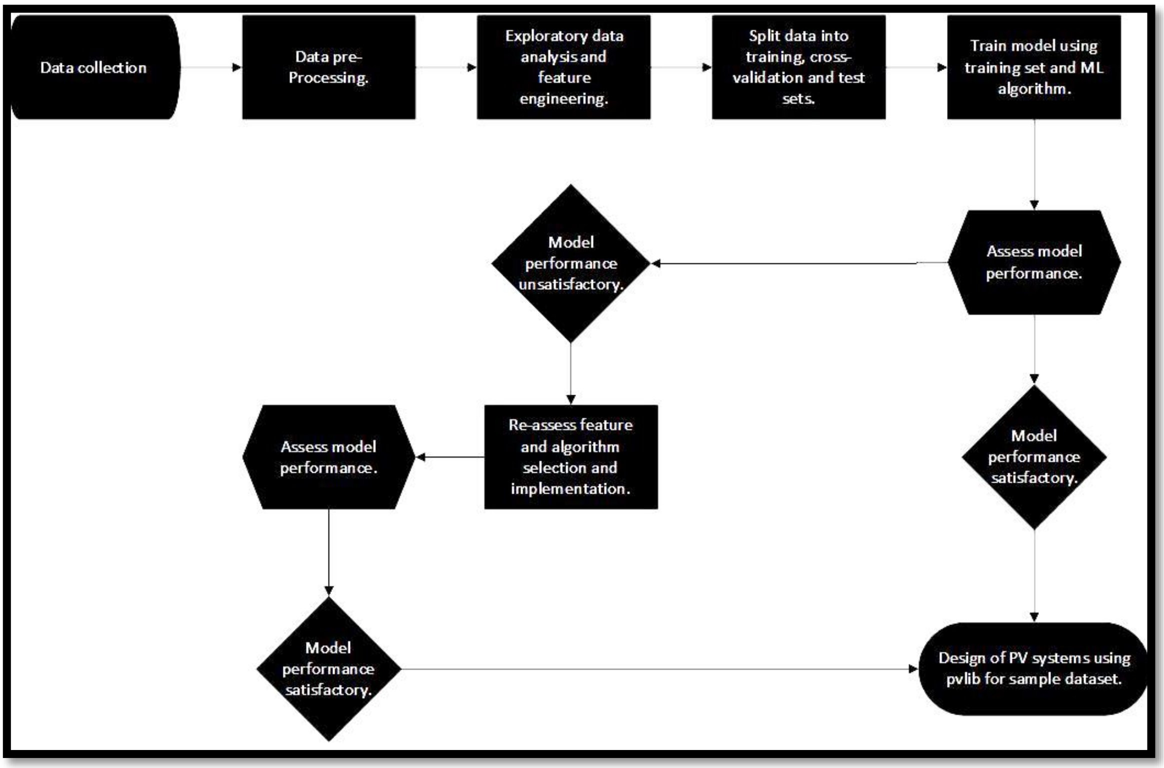
An open-source modelling framework, oemof, will be used to model a PV system for a small sample of residential homes in Trinidad and Tobago based on bi-monthly consumption data. The results obtained from these models will subsequently be utilized alongside weather data for the relevant period to determine the energy charge savings and potential earnings per month per consumer in the case of net metering. This project assumes that all excess electricity produced is sold back to the grid at retail value. Additionally, due the granularity of the data available, this study assumes the samples to follow a load profile of a typical residential household.

The range of dates across which the samples of consumption data span is April 2018 – May 2022. Although this sample size is very small, as net metering has not yet been implemented in Trinidad and Tobago, this research serves as a starting point for local stakeholders to perform further investigation. Different elements of the experimental procedure are outlined below.

2.1. **Process Overview**

The methodology for this thesis can be broken down into two major phases. In the first phase, the daily consumption of homes in Trinidad and Tobago was estimated using machine learning models. Subsequently, the pvlib python library was used to model PV systems at various sizes for each residential household sample. From the model key outputs such as the amount of excess electricity produced by the PV system and the demand charge savings were extracted for further analysis.

Figure 1: Process flow diagram for the methodology used to carry out research.



2.2. **Estimation of Daily Electricity Consumption**

Applications of machine learning to modelling renewable energy systems can often have a major limitation of insufficient data. To mitigate this issue, it has been suggested to combine traditional engineering modelling with machine learning practices. This paper has this limitation and, as a result, some synthetic data was generated using a machine learning model before the modelling of PV systems.

The local electricity company T&TEC has an online feature which allows consumers to analyze their bi-monthly energy usage over the previous 1.5 years. This dataset was obtained for a small sample of residential households in Trinidad and Tobago. For a subset (3 households) of the obtained dataset, daily consumption values were collected. This subset was then used to train a machine learning model to further estimate the daily consumption for those samples, as well as other samples in the dataset. The approach of estimating the daily consumption of the households was chosen, as opposed to a time series analysis, due to the data limitations present locally both for training and use of the model.

As the dataset being used for this analysis is relatively small, algorithms such as simple linear regression, ridge regression, support vector regression and XGBoost will be used. These algorithms were cited as being suitable for smaller datasets. Regularization and feature engineering were some of the methods employed to prevent overfitting the model.

2.3. **Modelling of Residential PV Systems**

To have full customization and transparency, an open-source energy modelling framework was selected for this study. Additionally, the use of the python programming language allowed for automatic looping and therefore modelling of multiple systems with reduced human input. The pvlib python library was selected for this study (Sandia National Laboratories and pvlib python Development Team, 2013-2021). In this section, a framework was designed to output details of PV systems of varying sizes for each of the samples. The primary driving factors in this optimization were therefore the incumbent cost of electricity and PV modules, the cost of auxiliary components, consumer demand and the rate of subsidization. Important outputs recorded from this model included any excess electricity generated as well as the demand charge savings achievable by the system.

2.4. **Calculating Economic Residential PV Potential.**

The indicator for economic potential selected for this study is demand charge savings. Using the results obtained in in Sections 2.2 and 2.3 above, as well as additional features such as weather, the energy charge savings achievable per consumer per month was determined.

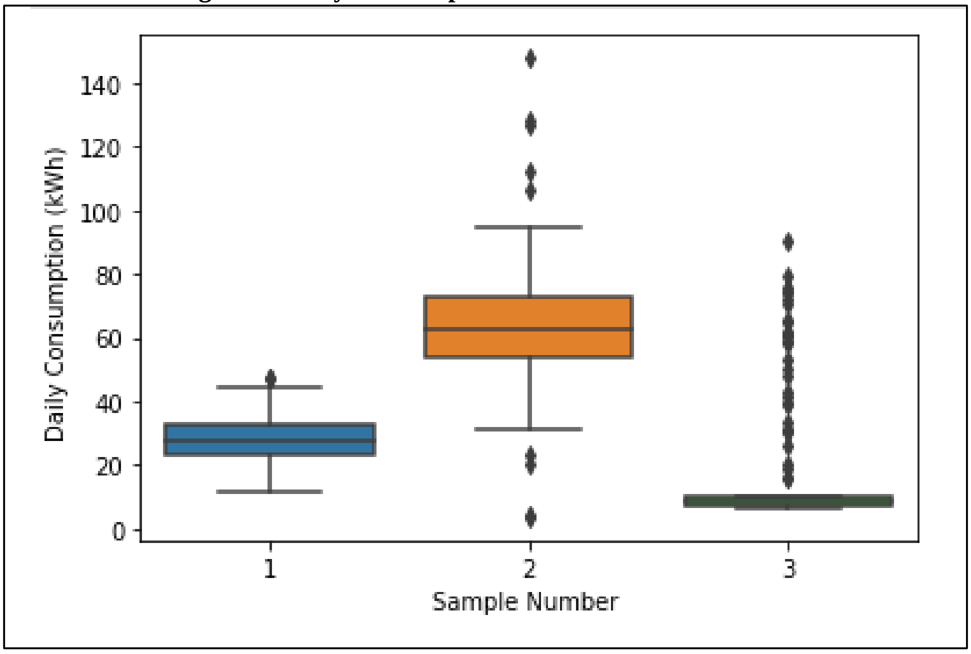
Weather datasets such as the precipitation, temperature, wind speed and humidity were gathered for the appropriate time frame. This data was gathered from a range of resources including the Trinidad and Tobago Meteorological Service (Meteorological Service of Trinidad and Tobago, 2018-2021) and other weather data collection (Piarco International Airport Station, 2022) and forecasting (AccuWeather, 2021) websites.

III. RESULTS AND DISCUSSIONS

3.1. **Estimating Daily Electricity Consumption using Machine Learning**

For this analysis, supervised learning methods were employed. As previously stated, bi-monthly and daily consumption data was collected via a survey. The dataset used for training this model included daily consumption readings over a 2–3-month period for 3 households at different energy usage levels. The usage levels of each household can be seen on the box plot in Figure 2. Due to the amount of data available, the dataset was augmented such that for all three samples, which were all taken in 2022, daily consumption was assumed to be in the same proportion to the bi-monthly consumption for the same period in the year 2021. This allowed for improved training of the model.

Figure 2: Daily Consumption of 3 different households



Daily consumption was the target variable for the model. Other features initially used as the independent variables in the training of the model included the date, the day of the week (Monday, Tuesday, etc.), the average temperature (°F), the total bi-monthly consumption (kWh) and the sample number. As seen in the correlation heatmap in figure 3, which shows highest correlation between features in red and the lowest correlation in blue, most of these features did not show a strong correlation with the daily consumption of each household. Therefore, the simple linear regression analysis was carried out using the bi-monthly consumption only, which showed the highest correlation to the daily consumption. However, it is important to note that the size and augmentation of the dataset may have had an effect on the ability to accurately assess the correlation between variables.

Figure 3: Heatmap showing the correlation of features considered for the model.

	Sample Number	Daily Consumption (kWh)	Bi-Monthly Consumption (kWh)	Avg Temp (°C)	Day of Week
Sample Number	1.000000	0.016313	-0.121968	-0.015389	-0.007182
Daily Consumption (kWh)	0.016313	1.000000	0.772294	0.016406	0.032140
Bi-Monthly Consumption (kWh)	-0.121968	0.772294	1.000000	0.008316	0.011813
Avg Temp (°C)	-0.015389	0.016406	0.008316	1.000000	-0.015766
Day of Week	-0.007182	0.032140	0.011813	-0.015766	1.000000

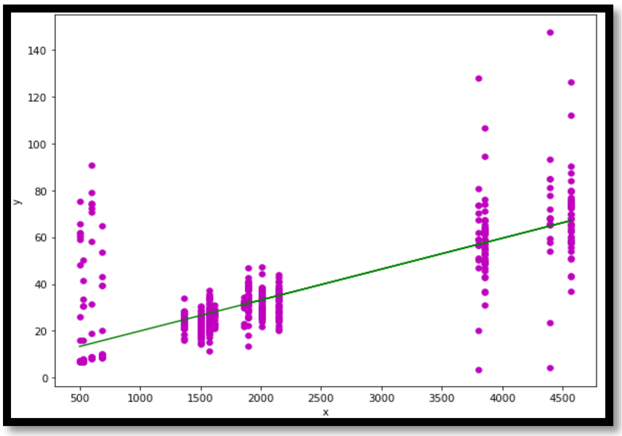
After determining the correlation between variables, a decision tree regressor algorithm was used to assess the relevance of each feature in relation to all the other features. In this analysis, each feature was selected as the dependent variable to be predicted using all the other features. The R2 value of each feature was then calculated, and the results are displayed in Table 1 below. Negative and low scores indicated that the variable is necessary to determine the electricity consumption of the household. High positive scores indicated that those features were less necessary.

Table 1: R2 scores for each feature as the dependent variable using the Decision Tree Regressor

Feature	R^2 Score
Sample Number	1.0
Bi-Monthly Consumption (kWh)	0.890
Avg. Temperature (°C)	-0.719
Day of the Week	-0.725

Based on the results obtained from the analysis of the feature relevance it was decided that the average temperature and day of the week would be used as features for the more complex regression models. Although the bimonthly consumption had a high R2 value, it was still used in these analyses due to its high correlation as previously discussed. Extreme outliers were removed prior to splitting the dataset into training and test sets to avoid overfitting and to test for generalization of the model. Cross fold validation with 10 folds were used in the training of the model. This is a method uses a resampling technique where the dataset is divided into k =10 subsets. The model is trained on the first set and tested on the remaining k-1 sets. The mean of the error of each set is them taken as the overall error for the model. The performance metrics used to assess this model included the R2 value and the mean squared error (MSE). The estimated coefficients for the regression model were found to be b0 = 6.74, b1 = 0.013 and the regression line can be seen in Figure 4.

Figure 4: Regression Line for Daily vs. Bi-monthly Consumption (kWh) for the training dataset



The initial MSE between the actual and predicted values of consumption was found to be 0.1457. The MSE between the predicted values and the average daily consumption values of the test dataset was also calculated and this value was found to be 0.2120. The ratio of the individual MSE to the average was therefore 0.6623. This ratio gives a measure of how significant the MSE is in relation to the actual daily consumption values, with values closer to 1 being preferential. In addition to performance metrics, the models were assessed using learning curves. This method was repeated using the Ridge Regression, Support Vector Regression and XGboost machine learning algorithms. The MSE using each algorithm is shown below in Table 2. Although the lowest MSE was produced by the Support Vector Regression algorithm, XGBoost was found to produce highest Relative MSE.

Table 2: MSE for each algorithm used to estimate daily electricity consumption

Model	MSE	Average MSE	Relative MSE
Linear Regression	0.1457	0.2120	0.6623
Ridge Regression	0.1331	0.1941	0.6858
Support Vector Regression	0.1285	0.1941	0.6620
XGBoost	0.1354	0.1941	0.6977

The learning curves for XGBoost and Ridge regression are shown below in Figures 5 and 6. Although XGboost yielded the best MSE score, based on the learning curves produced, the ridge regression algorithm was selected. This was because the learning curves for the XGBoost algorithm suggested that more data was required for training. In this case, the XGBoost algorithm may be overfitting the mode, which as previously discussed, is undesirable.

Figure 5: Learning Curve for the Ridge regression Algorithm

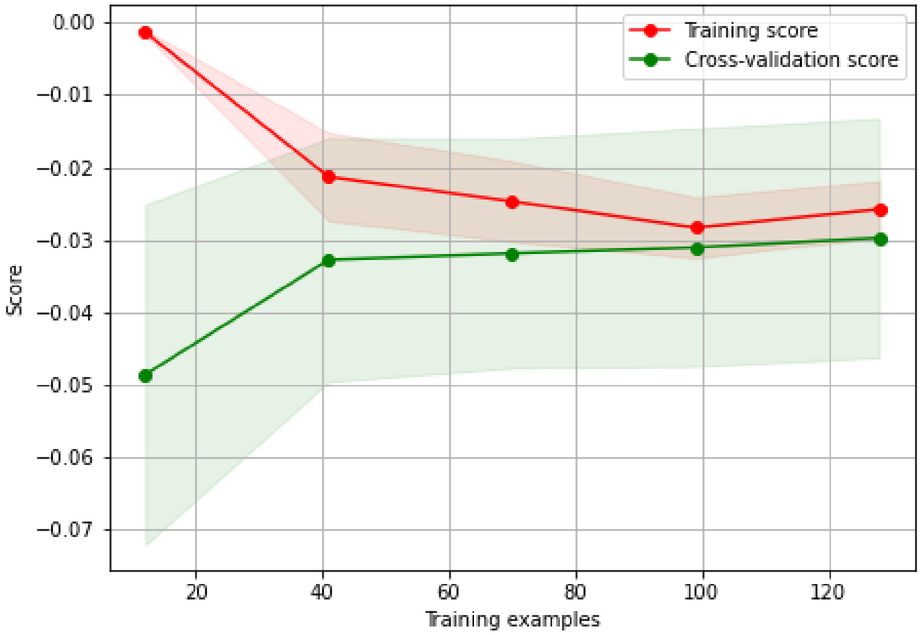
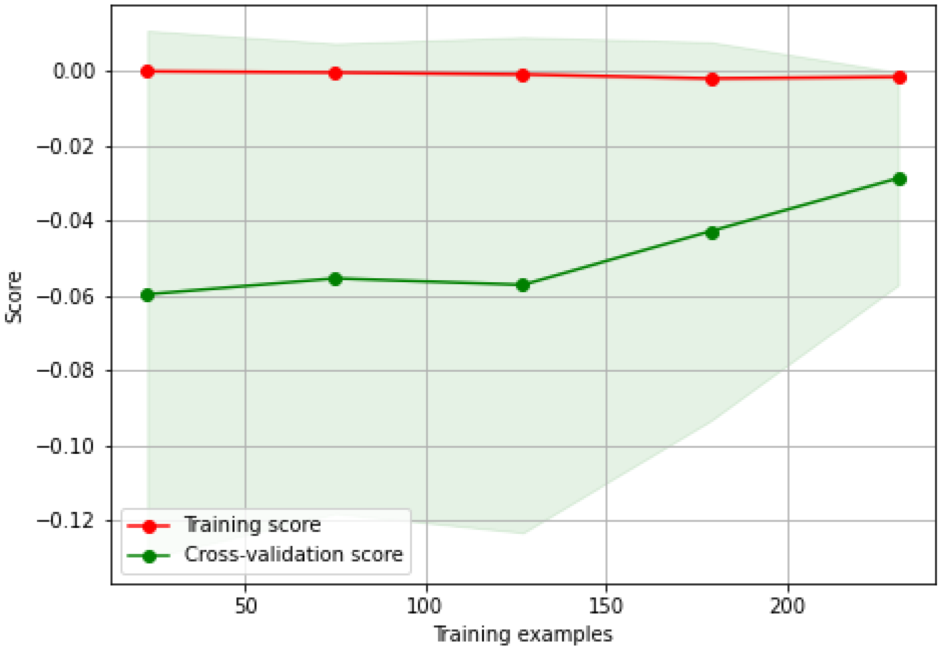


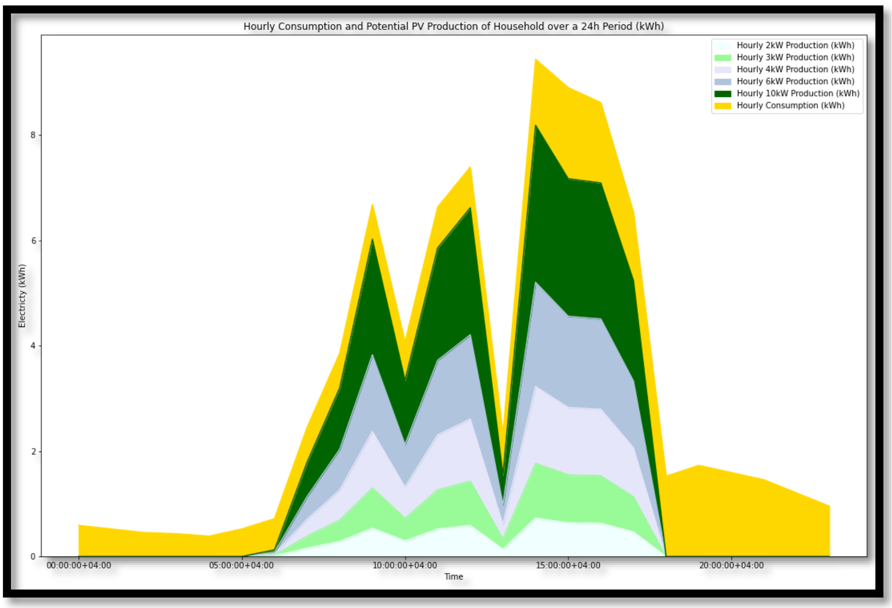
Figure 6: Learning Curve for the XGBoost Algorithm



3.2. **Modelling of Systems Using pvlib**

In this section, residential PV systems of 2kW, 3kW, 4kW, 6kW and 10kW are designed based on the output obtained from the daily consumption model. This program computes the demand charge savings for each system size based on the daily consumption estimates, local cost of electricity according to usage level, daily weather data and hourly Typical Meteorological year data from NREL. Solar energy data such as the DNI (Direct Normal Irradiance), DHI (Diffused Horizontal Irradiance) and GHI (Global Horizontal Irradiance) was fetched using modules from the pvlib library on python and validated using data from National Solar Radiation Database by NREL that coincided with the dates of the sample being analyzed. Additionally, the systems were designed using specifications of monocrystalline panels and inverters by the brand Renogy, as this is a brand used by a local PV company (Renogy, 2022). The model was designed using one sample from the dataset, the results of which are illustrated below. The model was subsequently tested on the remaining samples. The model can produce output for any system with more than two periods of bi-monthly data from 2018 or more recently. The model can be modified to allow for input of different brands of panels and inverters. Some key findings of these designs can be seen below in Figure 7.

Figure 7: Hourly Consumption vs. Production



As previously mentioned, the daily excess electricity (shown in Figure 7 above) was determined using the results obtained from the analysis above as well as a typical residential load profile. The monthly demand charge savings for each system size was subsequently calculated and is illustrated below in Figures 8 and 9.

Figure 8: Absolute Monthly Demand Charge Savings

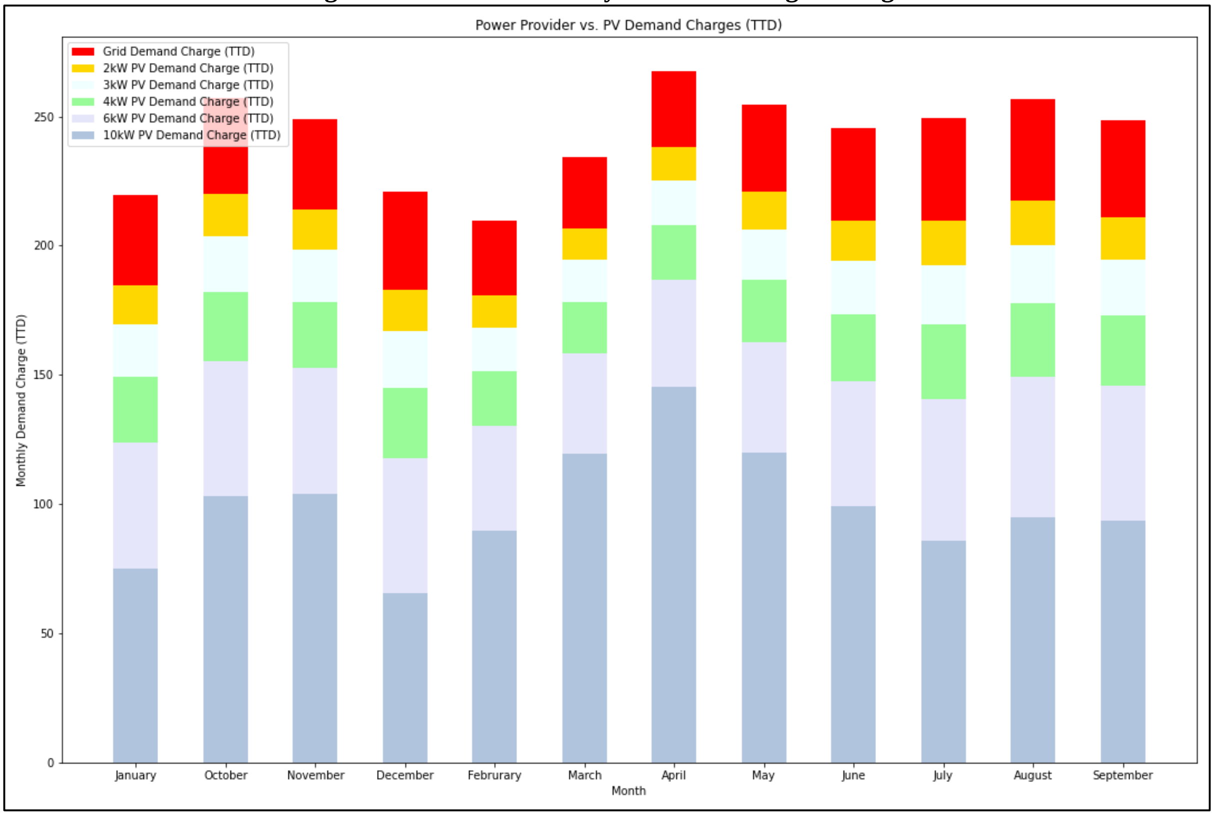
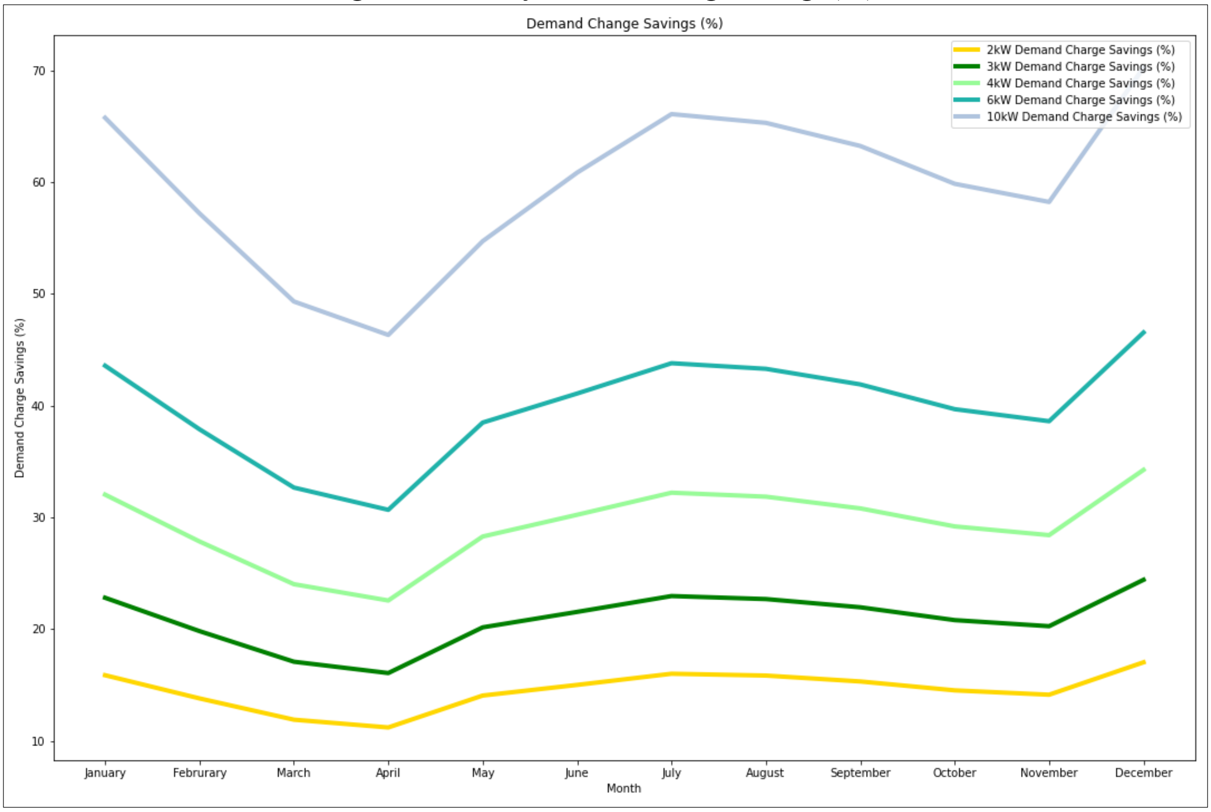


Figure 9: Monthly Demand Charge Savings (%)



3.2. **Estimation of Daily Consumption based on Bi - Monthly Data**

To effectively determine the most suitable size of distributed energy resources (DERs) or Renewable Energy Technologies (RETs), engineers typically require some information about the energy usage of the household through monthly or bi-monthly usage, smart meters or load typical profiles. The survey datasets of bi-monthly consumption required disaggregation into daily readings to determine how much excess electricity (and therefore demand change savings) can be achieved by the consumer. As this report did not consider the use of batteries, it was assumed that all excess electricity produced is sold to the grid. In this section, two methods of estimating the daily consumption of a household are compared. The first method is an excel sheet designed to estimate the daily (and hourly) consumption of an individual household based on user inputs. The second method makes use of the Ridge Regression machine learning model previously presented to predict the daily consumption based on the bi-monthly consumption as well as some supplemental features.

3.1.1. **Excel Load Profile Builder**

In this method of obtaining an estimate of the energy usage, an excel sheet is used in which the user is required to input data such as monthly usage, the weekday to weekend ratio of consumption trends and some measure of the load profile of the system in question. This method is advantageous in that it is simple and easy to use. It also outputs a detailed estimate of the energy usage of a system based on the user's inputs. A disadvantage to this method is the tedious process of being required to fill out a new excel sheet for every year for each household in question. Additionally, the user inputs required may be difficult to obtain. Researchers and engineers will be required to liaise with clients to determine their consumption habits during the week as compared to the weekends as well as their daily consumption habits. Furthermore, consumers who are not energy conscious may not even be able to provide accurate estimates.

3.1.2. **Machine Learning Algorithm**

To address some of the shortfalls of using the excel load builder, machine learning algorithms were considered as a new approach to estimating daily consumption based on a limited amount of information about the system.One of the disadvantages to using machine learning for this analysis includes the lack of required daily consumption data for improved performance (generalization) of the model. Additionally, the algorithm was employed using the Python programming language, which is not as widely used as Excel. This disadvantage may be mitigated through the development of interactive dashboards or web applications where the user can simply input the required information. This model is not only beneficial for ease of analysis of several samples over many years, as is done in this report, but can be beneficial to energy engineers in obtaining faster and more accurate information about a system using less user input data in lieu of detailed historical data or a smart meter.

3.1.3. **Comparison of Methods**

The Excel Load Profile Builder and Machine Learning approaches both have their advantages and disadvantages. Making an initial comparison, one can immediately see that the Excel analysis has the advantage of being able to produce estimates on a more granular scale. However, this shortcoming of the machine learning model may be overcome by the collection of more granular data for training the model. To compare the accuracy of each method, the root mean squared error (RMSE) was selected. It was found that the Ridge Regression model produced a lower RMSE of 0.133. The Excel-based load profile builder produced a RMSE of 4.78. Graphs showing the comparison of estimations made using the excel based and Ridge Regression approaches as compared to the actual consumption for one of the households with a median consumption level are shown in the Figures 10 and 11 below. It must be noted that although this sample represents the median usage of the datasets used, it may not represent the median usage of the population.

Figure 13: Comparison of Estimated vs. Actual daily electricity consumption using Excel load profile builder

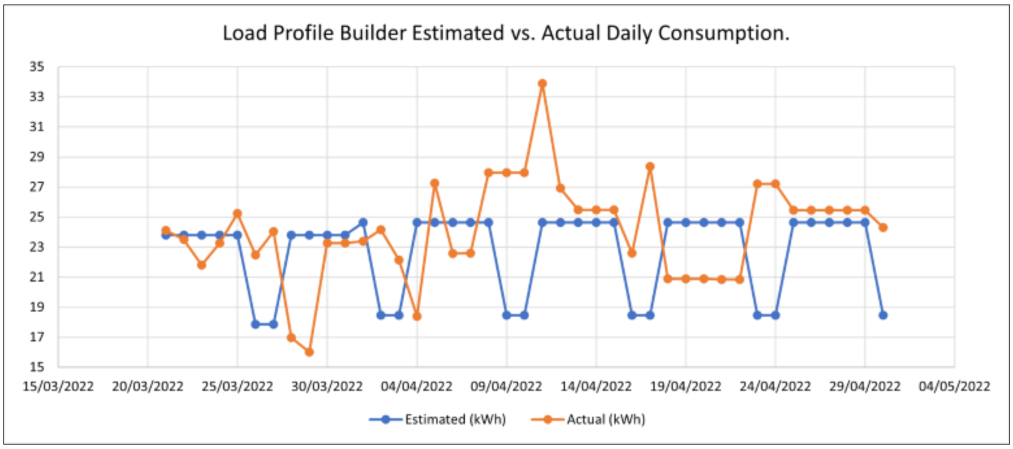
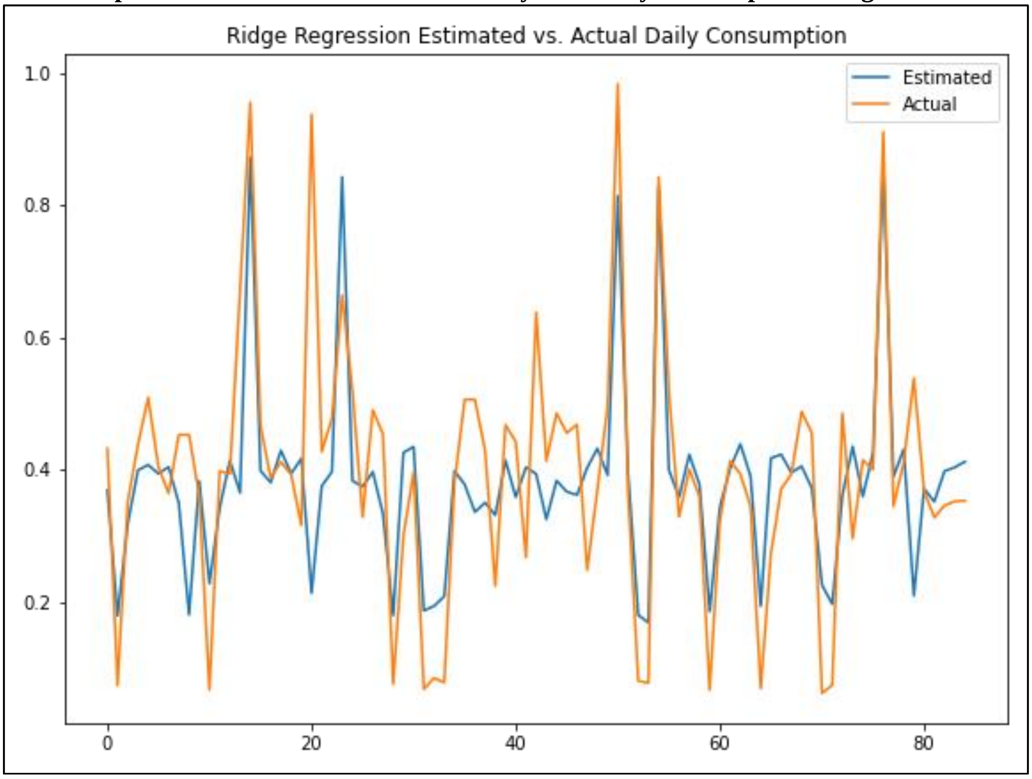


Figure 14: Comparison of Estimated vs. Actual daily electricity consumption using Machine Learning



3.2. **Modelling of Systems Using pvlib**

PV systems of size 2kW, 4kW, and 10kW were selected based on market research done for Trinidad and Tobago. It was determined, based on the offerings of local PV companies outlined on their websites, that there were the most frequently offered sizes. The 3 kW and 6 kW sizes were also included to provide a wider range of options for the consumer. This program was modelled such that once the user runs the program, they are prompted to upload a comma-separated values (csv) file of their bi-monthly data. From the outputs of the models obtained, displayed in the results section above, one can see that there will be demand charge savings for each size of PV system considered. However, it must be noted that not considered in the calculation of demand charge savings, is the capital cost of these systems as well as the payback period. As previously discussed, these are important socio-economic factors to consider when installing DERs. This presents an opportunity to improve on the model by adding features which account for the up-front affordability of the systems.

In contrast with proprietary software such as HOMER Pro, this model is highly specific to the energy framework of Trinidad and Tobago and very customizable. The model can also be an open-source method of exploring the benefits of photovoltaic energy. Solar companies may also use this model to implement an online feature, dashboard, or web application for their website to attract customers. In contrast with other online PV system sizing tools, such as the NREL PVWatts calculator, this model is specific to Trinidad and Tobago and can generate outputs based on the bi-monthly and daily data available to every customer of the local power producers. Additionally, the outputs of this model are on a more granular level.

The simulated demand charge savings may be used as seed data for a machine learning model which predicts demand charge savings based on simple features. This creates an avenue for improved estimates as it provides the opportunity to use actual data from households with PV systems installed, as opposed to modeled data. This may lead to more accurate estimations of demand charge savings that a consumer can achieve.

IV. CONCLUSION

In this paper, the economic potential for PV energy in Trinidad and Tobago was examined via the modeling and design of PV systems using data science principles. Two of the major barriers identified locally to the wide-spread adoption of renewable energy resources were the lack of data required to assess the effects of these systems on the technical and economic sectors of the existing electricity framework, as well as the upfront cost to consumers for installing these systems.

To mitigate some of these challenges, data science principles were used to estimate the necessary data required to model residential PV systems and subsequently calculate the demand charge savings possible from these systems. The model, which uses the Ridge Regression machine learning algorithm, estimated daily residential electricity consumption based on bi-monthly data available from T&TEC with a mean squared error of 0.1331 as compared to actual daily values for a dataset of 3 sample households. Collection of more data is necessary to improve the results of the model.

Subsequently, the pvlib python library was used to design PV systems of sizes 2kW, 3kW, 4kW, 6kW and 10kW were designed for a random sample of households in Trinidad and Tobago. This model can be used by consumers, power producers and local PV companies to help assess the suitability of a PV system for a particular household in a quick and open-source manner.

Conflict of interest

There is no conflict to disclose.

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