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Geographic decision support systems to optimize the placement of distributed energy resources

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Abstract

United States electric utility industry is moving toward a new power grid that will accommodate bi-directional energy flow and the incorporation of Distributed Energy Resources (DERs). Currently, utility companies lack tools to identify locations on the electric grid that can sustain DERs' adoption. This research explores the use of Geographic Information Systems (GIS), a class of tools for developing spatial models, with the aim of optimizing the placement of DERs. The intent of this research paper is to propose a Geographic Decision Support Systems (GDSS) model as a solution for the utility industry to assist in the DERs' portfolio choices and provide actionable information for utilities, system operators, and power producers. Claremont city has been chosen as the research site to demonstrate the applicability of the proposed model. This will also serve as the basis for future research.

Keywords: Component, smart grid, new power grid, DERs

1. Introduction

America's paradigm of one-way electric power generation and distribution is no longer sustainable [1]. The electric distribution system cannot meet the demand for cleaner power and more customer control of energy bills. Additionally, the existing one-way power grid cannot accommodate the growth in the penetration of Distributed Energy Resources (DERs) such as solar rooftops [2]. In 2014, the California Public Utilities Commission (CPUC), which is the state regulatory body responsible for electric utilities, asked for DERs integration into the electric distribution system. Later, in 2015, the CPUC issued a Distribution Resources Plan (DRP) ruling to change the current electric distribution system into a new system that accepts two-way energy flow between customers and their respective utility companies. The two-way grid allows customer involvement and their choice of new technologies for power generation, transmission, and consumption [3].

Despite the availability of new technologies for solar, wind, and hydro energy generation, along with other great improvements in the electric utility industry, the electric transmission and distribution systems have remained largely unchanged [4]. The key question is how utility companies can match supply and demand across the power grid, especially since the electric grid's bi-directional traffic congestion is growing rapidly. According to United States Department of Energy assessments, a superior system for matching supply and demand is necessary [5].

As stated in the "Analytic Research Foundations for the Next-Generation Electric Grid" 2015 report, there are many important characteristics that the next-generation electric grid system has to implement to improve the current grid system. Some of the features are combining generation and storage, involving customers, allowing DERs' adoption, and improving power quality. The report's producers developed a mathematical model that could be implemented in an effort to design, monitor, analyze, and control the next-generation electric grid system. The authors argued that this mathematical model could be used in a Decision Support tool to determine the emerging problems and instantaneously calculate corrective

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actions, which are extremely difficult tasks based on today's current system capabilities. The proposed model in the report aimed at ensuring optimal operation and robustness of the grid. Physics and engineering theories were the backbone of this model [6].

In the aforementioned report, GIS was only used as a display tool that showed the transmission grid, electricity interconnections, electric load, and the geomagnetically induced currents (GICs). We argue that, in addition to visualization, GIS is an extremely powerful tool that can be used for decision support, planning, and predictive modeling especially as utility companies are in the process of integrating DERs into the grid. Being able to build a custom GDSS solution that incorporate the mathematical model in the above report will enable these capabilities to meet utilities' specific geo-processing needs.

The U.S. Department of Energy Office of Science is calling for researchers to assist the utility industry in its transition to a 21st century grid. In response to the call, our paper addresses this research question: "How can GIS be employed to optimize the placement of DERs?" In this research paper, we develop a GDSS model for the utility industry to aid in DERs portfolio choices and provide actionable information for utilities, system operators, and power producers. The intended audiences for this research are utility corporations, state-level decision-makers, and other stakeholders who are concerned about the future of the United States electric power system.

2. Model Design

This study proposes a GDSS solution to assist in DERs portfolio choices and provide actionable information for utilities, system operators, and power producers. The goal is to optimize the placement of DERs considering the electric circuit capacity constraints, the households' solar rooftops potential electricity output, and the projection of households' profiles adopting DERs.

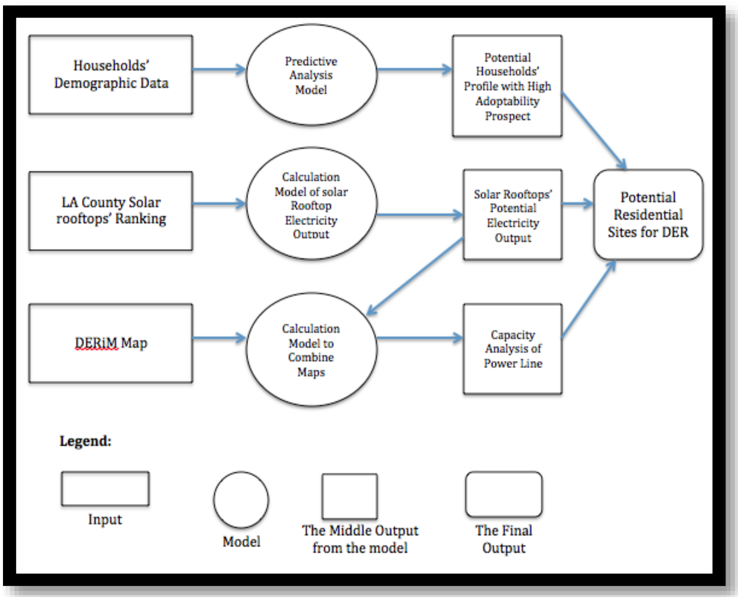

Fig. 1. Geographic decision support system model to optimize DERs' placement.

Input data is the households' demographics, SCE parcel map that includes power electric lines and the potential solar energy with the capacity in kilowatts for a specific area in Los Angeles County, USA. Based on the input data, the following three sub-models are created as shown in Fig. 1:

1. A predictive analysis model based on households' demographics data to yield a projection of households' profiles adopting DERs.
2. A model to calculate households' solar rooftops electricity output based on LA County solar rooftops' rankings.

3. A model to combine electricity output from the current system with the solar rooftops' potential electricity yield.

The outputs are property location and boundaries (geospatial data), proximity to power lines, and potential residential sites suitable for DERs' adoption. The required data is mainly retrieved from the Los Angeles County GIS Data Portal and the SCE's DRiEM.

The proposed predictive model can be applied for all Energy Informatics use cases such as commercial, residential, and factories. In this paper, we chose to focus on the "residential" parcel type in LA County due to the data availability. We further chose to use Claremont City as a demonstration to provide an evidence for our research findings. Claremont city is located in the eastern border of Los Angeles County in California. According to 2014 United States Census, the population is 36.054. The main reason for choosing this city is the data availability. Electricity service is provided by SCE in the city of Claremont. Hence, data is available and accessible from SCE DERiM and LA County solar map. More details about the model design are illustrated in Appendix A.

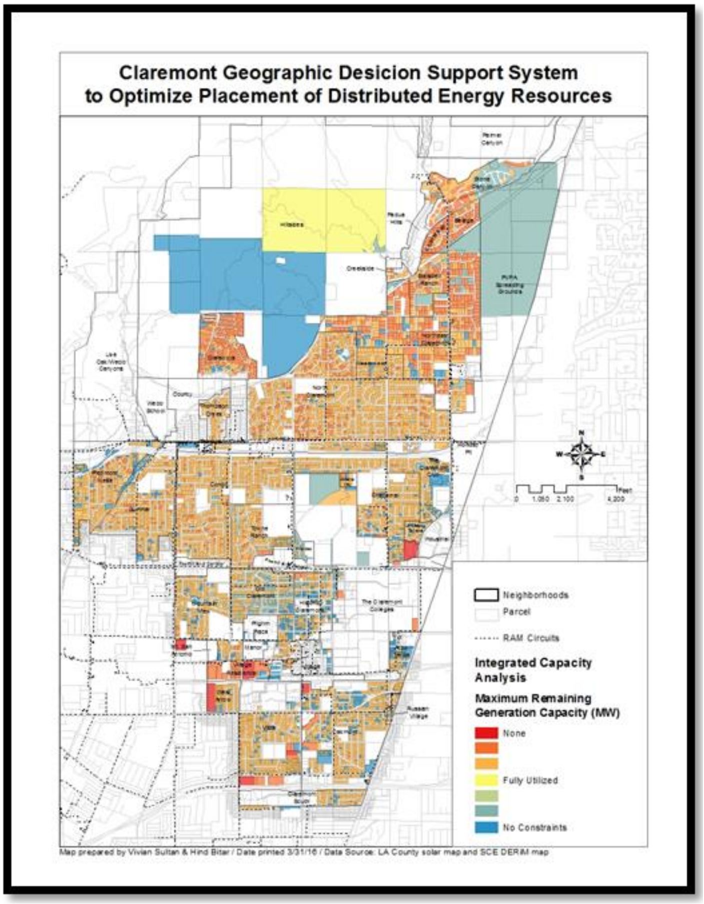

Fig. 2. Claremont GDSS model.

The Design Model Output:

To perform the capacity analysis and identify the suitable areas for DERs' residential adaption in Claremont City, ArcMap 10.3 software is solely utilized. The inputs for the final result are the potential households profile with high adoptability prospect, the solar potential electricity, and the power line capacity constraints. For demonstration purpose, the streets, parcels, and neighborhood names were added to Claremont map as shown in Fig. 2 and Fig. 3. Seven graduated colors in the map symbology tab have been selected to show the circuits' constraint levels assuming the maximum solar potential per parcel.

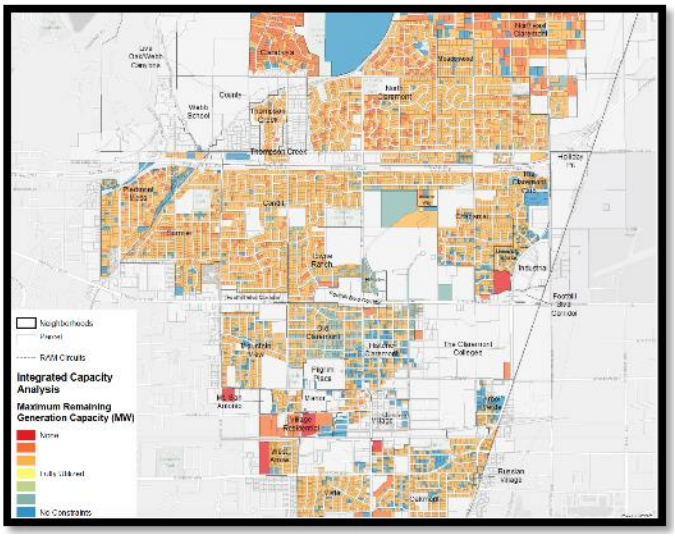

Fig. 3. Claremont City design model output.

3. Analysis and Results

According to ESRI [7], "the Hot Spot analysis tool calculates the Getis-Ord Gi* statistic for each feature in the dataset". In this case, the feature is the electric circuit's hosting capacity. The resultant Z score tells us where the electric circuits with either high or low capacity constraints values cluster spatially. This tool works by looking at each circuit line's hosting capacity within the context of its neighboring electric circuits capacity constraints. An electric circuit with high capacity constraints is interesting, but may not be a statistically significant hot spot. To be a statistically significant hot spot, an electric circuit will have high value of capacity constraints and be surrounded by other circuit lines with high constraints as well. Thus, statistically significant hot and cold spots are worth investigating. The Getis-Ord local statistics is given as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}}$$

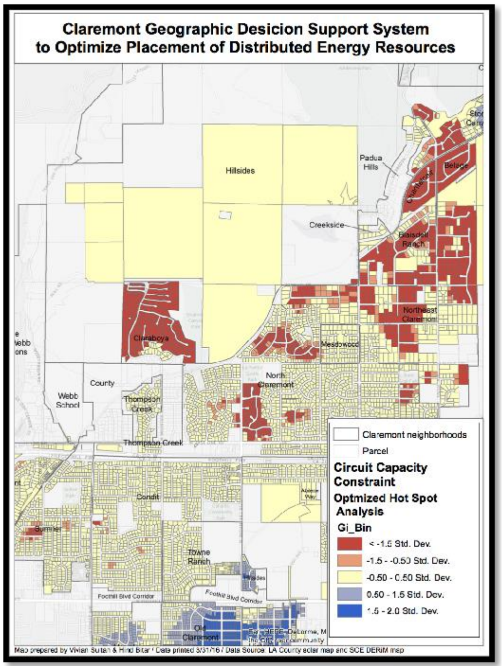

Fig. 4. Hosting capacity.

Optimized Hot Spot Analysis

Assuming the maximum residential adoption of solar rooftops in the city of Claremont, analysis indicates that there are several hot and cold spots of electric circuits' hosting capacity. However, as illustrated by the yellow parcels in Fig. 4, the majority of spots were neither hot nor cold.

The capacity constraint hot spots appeared, as shown in Fig. 5, in areas such as North, and Northeast Claremont. Also, as demonstrated in Fig. 5, additional hot spots appeared in neighborhoods such as Chantelcair, Belage, Claraboya, and Blaisdell Ranch. It's important to note that the hot spots (red parcels) imply higher statistically significant electric circuit capacity constraints than the orange parcels.

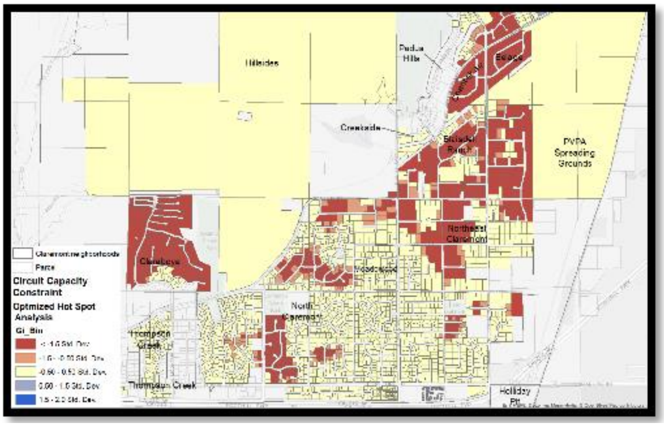

Fig. 5. Capacity constraint hot spots in city of Claremont.

As for the cold spots, sufficient capacity appeared primarily in the neighborhood of the Hillsides, Claremont club, Arbol verde, Oakmont, Old and Historic Claremont. Darker blue neighborhoods, or cold spots, are likely to experience a superior hosting capacity than the grey spots as shown in Fig. 6.

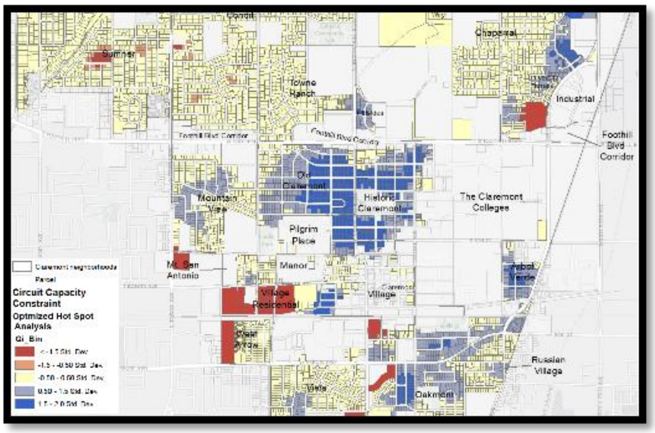

Fig. 6. Hosting capacity cold spots in city of Claremont.

Utility companies can utilize this GDSS model to prioritize infrastructure work in locations such as Northeast Claremont and Blaisdell Ranch where there is a greater need to increase the hosting capacity of the electric circuit. Also, if we look closely into the maps, it's easy to detect residential areas with adequate hosting capacity that is appropriate for solar rooftops adoption. Hillsides, Claremont club, Arbol verde, Oakmont, Old and Historic Claremont are good illustrations of this instance.

Considering the electric circuit current hosting capacity scenario in the city of Claremont and the solar rooftops maximum adoption scenario, the following tables compare the priority with respect to the infrastructure work needed in each case.

Table 1. The maximum residential solar rooftops adoption scenarlo

Circuit Name	Infrastructure Work Priority
PADOVA	1
BIG CONE	2
CALSPAR	3
FORBES	4
ANAWALT	5
NEIBEL	6
ALAMOSA	7
ROCK	8
BONTANIC	9
KINGSLEY	10
PITZER	11
WINTHROP	12
LIMBER	13
BASELINE	14
POMALL	15
LEHIGH	16
PALMER	17
MOAB	18
AVENIDA	19

Table 2. The existing scenario

Circuit Name	Infrastructure Work Priority
MOAB	1
BIG CONE	2
PADOVA	3
PALMER	4
LEHIGH	5
KINGSLEY	6
CALSPAR	7
AVENIDA	8
WINTHROP	9
BASELINE	10
LIMBER	11
BONTANIC	12
FORBES	13
NEIBEL	14
POMALL	15
PITZER	16
ALAMOSA	17
ROCK	18
ANAWALT	19

In the current residential solar rooftop adoption scenario, we can see that MOAB circuit is on the top priority list for infrastructure work due to its present need for additional capacity on the circuit line. While in the maximum residential solar rooftops adoption scenario, MOAB circuit ranked as #18 on the priority list and PADOVA ranked as #1 in terms of the requirement for added capacity.

4. Discussion

The model proposed in this paper used ESRI's households' demographics, the published SCE parcel map, and LA County solar map to develop a GDSS model that can optimize the placement of DERs. This could potentially save time and resources for utilities by early identification of locations with sufficient capacity and existing infrastructure to accommodate DERs adoption. Electric circuits needing additional infrastructure work and regions where DERs may provide net benefits can, thus, be prioritized. However, one limitation of this model is that it deliberated residential DERs adoption use cases and did not consider other use case types such as commercial buildings and factories. A second limitation is that the effect of DERs producing energy is the only element considered in the proposed model to impact the capacity of the electric circuit. Thus, the impact of electric vehicle, a DER that consumes energy, is not considered in this case.

5. Concluding Remarks

This study aimed at addressing "How can GIS be employed to optimize the placement of DERs?" To answer the research question, we have defined GIS, investigated its applications in utilities, and examined how it was employed for predictive modeling in different sectors. A GDSS model has been developed utilizing ArcMap 10.3 software to assist utility companies in prioritizing locations, which need infrastructure work, and detecting regions where DERs may provide net benefits. The hot spot analysis revealed areas where the electric circuits' capacity constraint is statistically significant and those with superior hosting capacity to allow DERs' adoption. Future research has been recommended to build on ArcMap source code and create a custom solution for the utility industry to forecast and balance electric power across the grid.

From this research, we conclude that not only can GIS be used as a display tool, but it also offers a solution to analyze the electric grid distribution system. Our model provides evidence that GIS can perform the grid's integrated capacity analysis in replacement of the software currently employed by utilities. If additional funds and data are made available, a custom GIS solution can be developed to optimize the placement of DERs in the entire state of California.

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Appendix A: An example appendix

A.1. Sub-Model 1: A predictive model to forecast customer adoption of DERs

A. Data selection and acquisition

1. Solar parcel data

LA County is the data source for the solar parcel data. The link to LA County solar parcel database is http://solarmap.lacounty.gov/

LA County solar map is the first data input and it includes the following key data elements:

- **Total Roof Area and Area Suitable for Solar**: This data is estimated for each parcel from a countywide 2006 solar radiation model. The standard calculates and ranks incoming solar radiation every 25 square feet in the county, using roof pitch, orientation, and shading from surrounding structures and trees to provide the best estimates possible.
- **Potential Solar System Size:** This is calculated from the parcel's optimal roof area and panel specifications. The calculations are based upon 18.1% efficient SunPower 225 panel.
- **Solar Potential Annual Output:** This is calculated by multiplying potential system size by 5.3 hours of generation per day and a 75% Performance Ratio which takes into consideration electrical losses, alternating current conversion (AC) and other environmental factors like soiling.
- **Potential Cost Savings:** This is computed based upon selected rates for each utility.

2. Customers' expenditure data

The Environmental Systems Research Institute (ESRI) is the data source for the Customers' expenditure and demographics data. ArcGIS online subscription is required to get access to this database. ESRI's United States customers' expenditure data is based on the latest Consumer Expenditure Surveys (CEX) from the Bureau of Labor Statistics. Data is reported at the block level and includes total expenditures, average spending per household, and a Spending Potential Index (SPI).

3. Customers' demographic data

Customers' demographics database from ESRI is the third data input for this model and it includes the following data categories:

- Population demographics data such as age, sex, race, Hispanic origin, labor force, educational attainment, marital status, civilian labor force and employment by industry and occupation.
- Household data such as total households, total family households, average household size.
- Income data such as household income, per capita income, age by income, disposable income, and net worth.

B. Data preparation steps

1) Data are extracted and loaded into ArcMap to show three map layers. The first layer showed LA county solar data by parcel while the other two layers showed the customers' expenditure and demographics data by block.
2) Parcels' data from LA County solar map were combined with customers' expenditure and demographics data. Using ArcMap model builder tool, the following model was designed to spatially join the three map layers and provide a table output in Dbf file format.

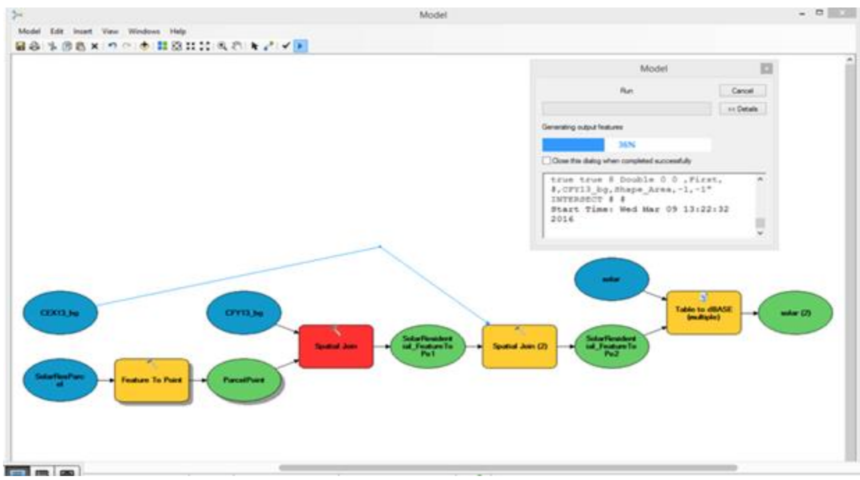

Fig. 7. ArcMap Model Builder to add demographic and expenditure data to each parcel.

3) Unnecessary and null fields are eliminated from the dataset to reduce the file size to 2.78 GB.
4) The output file was saved as a geodatabase and exported as a txt file format.
5) The txt file was converted to CSV and loaded into Microsoft Azure Machine Learning platform.
6) A SQL query was written to pull the current installations of solar rooftop (JSON file) from LA County database. This dataset is used to train the model in Microsoft Azure.
7) The output JSON file was converted from previous step to CSV file format using Python code.
8) A second model was constructed in ArcMap Model Builder to get an output map layer showing the solar installations in LA County with their respective demographics and expenditure data by parcel. The Dbf output file was converted to CSV file format following the previously mentioned steps. Finally, the installation data was joined with the entire dataset to identify which households have solar rooftops.

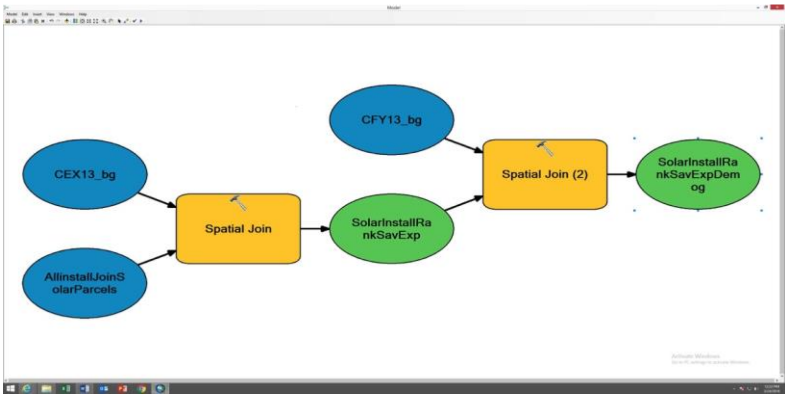

Fig. 8. ArcMap Model Builder to add demographics and expenditure data to parcels with current solar installations.

Utilizing logistic regression, a model has been designed in Microsoft Azure machine learning with the following key variables:

1) Dependent variable: Customer’s adoption of the solar rooftop, where the model output is either “yes” to the solar rooftop adoption or no (Y/N).
2) Independent variables: such as the solar system cost saving, solar system value, electricity usage, customer’s demographics and expenditure data.

A.2 Sub-Model 2: A model to calculate households’ solar rooftops electricity output based on LA county solar rooftops’ rankings

LA county solar rooftops’ rankings from the Los Angeles County GIS data Portal website is used to calculate the solar rooftops’ potential electricity output. There are four main ranks defined by the utility companies (Los Angeles County GIS data Portal, 2016):

3) Rank 1 is the square feet of roof receiving excellent solar input, which is bigger than 1.4 million watt Hours per square meter.
4) Rank 2 is the square feet of roof receiving good solar input, which is between 1.15 and1.4 million watt Hours per square meter.
5) Rank 3 is the square feet of roof receiving poor solar input, which is between 950,000 and 1.15 million watt Hours per square meter.
6) Rank 4 is the square feet of roof receiving negligible solar input, which is smaller than 950,000 million watt Hours per square meter.

According to the photovoltaic software website, rank 1 and rank 2 are the only ranks included to calculate the solar potential electricity. The four key elements to compute the energy (E) resource in KWh are as follows (Photovoltaic software, 2016):

1) A = Total solar panel Area (m^2), which is rank1+rank2
2) r = solar panel yield (%), which is the solar panel efficiency and it is equal to 0.181
3) H = Annual average solar radiation on tilted panels (shadings not included), which is constant for

Claremont city (equal to 2025.75).

- The PVWatt calculator is used to estimate the energy production and cost of grid-connected photovoltaic for Claremont City, and it is equal to 5.55. To calculate the annual average, multiply by 365.

4) PR = Performance ratio, coefficient for losses (range between 0.5 and 0.9, used default value = 0.75)

Hence, the following formula is used to compute the solar rooftops' potential electricity in Arc Map. Then, multiply by 1000 to transfer from KW to MW. Two fields are added in ArcMap attribute table to perform this calculation.

$$\boxed{E=A*r*H*PR}$$

E = DER's total energy output

A = Total solar panel Area

r = solar panel yield

H = Annual average solar radiation on tilted panels

PR = Performance ratio

A.3 Sub-Model 3: A model to combine electricity output from the current system with the solar rooftops' potential electricity yield

The output map from sub-model 2 is spatially joined with DERiM map (DERiM Web Map, 2016) in order to do the integrated capacity analysis by circuit line. The following formula is used to compute the maximum remaining generation per circuit line (Southern California Edison, 2016). The result demonstrated the power line capacity constraints. A field is added to the map attribute table to perform the computation for every parcel.

Maximum Remaining Generation Capacity = Current Capacity Load - (Solar Potential + Existing Generation)