OptiSolar: Using Artificial Intelligence to Evaluate the Solar Potential of Urban Landscapes

Kenny Hermus, Saadya Rao, Ethan Yeung, and Yixiang Li
The Pennsylvania State University

Introduction

Over the past century, there have been rampant concerns regarding the state of the environment. The world is consuming its nonrenewable resources at an ever-increasing rate, which is physically unsustainable and detrimental to the environment. These nonrenewable resources release pollutants, such as greenhouse gasses. Some of these gasses, such as carbon dioxide (CO2) and methane, are currently key contributors to a variety of issues, such as global warming, ocean acidification, and human illness. According to a Harvard study, "Researchers estimated that exposure to particulate matter from fossil fuel emissions accounted for 18 percent of total global deaths in 2018" (Burrows, 2021). In the U.S. alone, respiratory illnesses and heart disease linked to the burning of fossil fuels lead to over 200,000 early deaths and $800 billion per year in health costs (Limaye). The United Nations estimates that cities are the top contributors to the energy consumption and greenhouse gas emission crises. Although urban areas only make up 2% of Earth's surface, they consume 78% of the world's energy and generate 60% of greenhouse gas emissions.

Thus, there has been a push towards finding a more sustainable method of energy production. The source of this sustainable energy comes from renewable resources, which include biomass fuel, hydropower, geothermal power, wind energy, and solar energy (National Geographic Society, 2023). Technologies that utilize these renewable resources have been continuously developed, creating what is referred to as green energy. This mutual connection between economic investments, human health, and technological advancement serves as a prime example of coproduction as explained by Ruha Benjamin in 'Introduction Discriminatory Design Liberating Imagination'. This coproduction would have a significant impact on reducing polluting fuel emissions while keeping up with the high energy demand. Although each of the renewable energy sources has its own advantages, an approach to providing green energy for urban landscapes provides additional parameters that favor certain resources over others.

Compared to other renewable energy sources, solar energy is more adaptable to urban environments. Solar panels work by converting sunlight into electricity via the photovoltaic effect. These panels can be installed on rooftops, building facades, or other unused spaces, making them ideal for densely populated urban areas, and being very space efficient. Additionally, since the energy does not have to travel as far, energy loss during distribution and transportation is minimized (Crail, 2023). They are typically installed in areas known to have high solar productivity – a measure of the amount of electricity the solar device or system actually produces.

That being said, the problem is as follows: There is too strong of a reliance on nonrenewable resources in urban landscapes and the incentive to switch to renewable energy is low due to the amount of time and money needed for solar capacity identification. Given all of the sides of this issue, the goal is to globally accelerate the identification of prime investment locations for new solar capacity in urban areas, promoting sustainability and clean energy economic growth. Increased solar adoption directly enables reduced reliance on nonrenewable resources. This will be done by utilizing historical weather data to predict the solar potential of an urban environment through neural networks and cognitive systems using data from SolarAPI.

Literature Review

Nowadays, the consumption of non-renewable resources to generate electricity is still the primary method of power generation. However, while people enjoy its convenience, it also brings many adverse effects. Therefore, there is a movement towards seeking more environmentally friendly and sustainable ways of generating electricity, of which solar power is an example.

Nonrenewable Energy

Nonrenewable energy consumption contributes significantly to environmental degradation and climate change. A study conducted in Argentina provides evidence of this, revealing that nonrenewable energy consumption contributes to CO2 emissions and environmental degradation (Adebayo, 2021). The finding is supported by another study that investigates the impacts of nonrenewable energy and trade on environmental quality in selected G-20 countries (“climate change”). The study found that coal, gas, and fuel increase CO2 emissions. Furthermore, an article on ACCIONA discusses the environmental impact of nonrenewable energies, suggesting that the use of nonrenewable energy sources hastens climate change and global warming (“climate change”).

The world is currently facing a global energy crisis of unprecedented depth and complexity, as reported by the International Energy Agency (IEA). This crisis has major implications for markets, policies, and economies worldwide. A report by Energie Advisor states that the energy crisis is a result of general overconsumption (Samsa, 2022). The article on Our

World in Data (2023) discusses the world's energy problem, suggesting that the world lacks safe, low-carbon, and cheap large-scale energy alternatives to fossil fuels. The article highlights two major energy problems that the world is currently facing. The first problem, which receives the most attention, is the link between energy access and greenhouse gas emissions. The second problem, which is just as significant, is that hundreds of millions of people lack access to sufficient energy entirely, leading to severe consequences for both individuals and the environment.

This lack of access to energy is a pressing issue that needs to be addressed alongside the environmental impacts of energy consumption. The article suggests that until safe, low-carbon, and cheap large-scale energy alternatives to fossil fuels are standardized, these two global energy problems will persist. Therefore, this project "OptiSolar" can help alleviate the environmental crisis and energy crisis caused by the consumption of non-renewable resources to a certain extent.

Solar Energy

Solar energy has been a topic of extensive research due to its potential as a renewable energy source. The National Renewable Energy Laboratory (NREL) has conducted extensive research on various aspects of solar energy, including photovoltaics, concentrating solar power, solar grid, and systems integration, and market research and analysis. Similarly, in 2019 the MIT Energy Initiative focused its research on the future of solar energy, particularly on photovoltaics (PV) and concentrated solar power (CSP). A significant finding from the United States Department of Energy suggests that solar could account for as much as 40% of the nation's electricity supply by 2035 and 45% by 2050 ("Solar futures study").

Solar Energy and Artificial Intelligence

Many researchers are trying to apply artificial intelligence to solar and other renewable resources to improve the efficiency of their power generation and reduce the cost of using renewable resources. A paper published in the IEEE International Conference on Environment and Electrical Engineering examined the state-of-the-art artificial intelligence (AI) techniques and tools in power management, maintenance, and control of renewable energy systems, specifically for solar power systems. The paper identified several AI systems often used in solar predictions, including the Artificial Neural Network, Backpropagation Neural Network, Adaptive Neuro-Fuzzy Inference System, and Genetic Algorithm. Among these techniques, ANN stood out due to its short computing time, higher accuracy, and generalization capabilities over other modeling techniques. This would translate to cost efficiency over other modeling techniques. The Solar Energy Technologies Office Fiscal Year 2020 (SETO, 2020) funding program supports projects that will improve the affordability, reliability, and value of solar technologies on the U.S. grid and tackle emerging challenges in the solar industry (Khan, 2023). This program funds projects that advance early-stage photovoltaic, concentrating solar-thermal power (CSP), and systems integration technologies, and reduce the non-hardware costs associated with installing solar energy systems.

Due to the severe shortage and environmental pollution of non-renewable resources, the urgency of seeking renewable resources, and the outstanding advantages of solar energy in renewable resources, this project chooses solar energy as the research focus. At present, there have been some important advances in the application of AI in solar energy and geography, which provide valuable references and references for the projects. For example, the project will be based on the Google Solar API, a tool that can determine whether a location is suitable for installing solar panels based on the data collected. By learning from previous research results, we can carry out new research and development on this basis, with a view to making new breakthroughs in the field of solar energy and renewable energy

Methodology

This section will allow for dataset consumers and creators to understand the processing and usage done on the data that fits the needs of OptiSolar. Given the scope of this project, instead of creating a datasheet as described by Gebru et. al in ‘Datasheets for Datasets’, high standards of transparency and clarity will be maintained throughout this section for the sake of stakeholders’ understanding. The high level methodology for OptiSolar’s build and functionality is as follows: after creating the dataset and building the frameworks for the neural network and ACT-R model, the dataset was fed to Google’s Solar API and Tomorrow API to obtain insights used to train the pre-initialized feed-forward neural network. Then the neural network provided a rating for creating a color overlay for the map in the initial dataset. For testing, individual points of latitude and longitude were input into the application from urban areas with non-determined levels of solar productivity. Mapbox was used to display the final color coded map for the user to view.

Dataset Creation

The initial dataset for training was created by manually taking 10 coordinates of blocks from the 10 largest cities in the United States (x by x meters), which have already been marked by previous solar productivity mappings with the level of solar potential. For example, NY Solar Map and Project Sunroof were used to determine these levels of solar productivity. The x by x meter area was then split into four quadrants each with their own coordinate center of latitude and longitude. Then these coordinates were fed to Solar API to obtain building insights that were necessary for generating the neural network output. Solar API provides historical weather data based on the coordinates given in the form of .json files. The inputs of maximum sunshine hours, cloud cover, and snow accumulation were determined to be important for the neural network output. These inputs gave the most relevant data for determining the threshold for determining satisfactory levels of solar panel placement.

Neural Network

The overall design of the neural network is feed-forward with categorical cross-entropy loss for updating the weights. The Solar API inputs, as provided earlier, were assigned an input node for the neural network design. The hidden layer contains six nodes and the output layer contains one. Xavier initialization was used to initialize the weights. This provided a controlled random initialization before training the network and optimizing the weights. ReLU activations were done on all the hidden layers to introduce non-linearity between the inputs and output. A sigmoid activation was done for the output layer to get a number from 0 to 1. This output represents the rating given by the neural network. A rating from 0 to 0.3 (inclusive upper bound) means that the given location is a poor choice for placing solar panels. A rating from 0.3 to 0.6 (inclusive upper bound) means medium rank for placement and anything above 0.6 is high rank for solar panel placement. For updating the weights through backpropagation, categorical-cross entropy was used to minimize loss since this is a multi-class classification task.

Testing and Results

First, coordinates of latitude and longitude in WGS 84 standard as well as the radius (in meters) of the area to be examined were given. This created a square with a side length of 2 times the radius centered at the latitude and longitude. After feeding this information to the application, a map with a color overlay of areas showing solar productivity was given through Mapbox. A poor rating from the neural network resulted in a red color overlay for that particular area in the map to provide a better visualization. A medium rating resulted in a yellow color overlay and a good rating resulted in a green color overlay.

Man - Genre of the Human

The field of artificial intelligence is predicated on the understanding of how humans think. Whether it be neural networks or reinforcement learning, the concept of human intelligence is the cornerstone of computational learning. However, this also means that any systemic issues with the accepted view of human intelligence bleed over into the study and development of artificial intelligence. These types of issues can be most easily perceived through the ethical problems found within artificial intelligence, such as dataset biases or algorithmic fairness (Huang et al., 2023.)

Sylvia Wynter, a Jamaican woman known for her works as a journalist, critic, and philosopher, coined the term ‘Man - Genre of the Human’ as a method of defining what it means to understand human existence. Wynter believes that the modern understanding of what it means to be a ‘Man’ leans largely towards the traditional white man, excluding those who stray away from this group. Wynter states that this conceptualization originates from the Eurocentric worldview perpetuated by European colonization. Through colonization, the Europeans were able to force their values on indigenous groups, destroying their cultures, and treating them as subhuman. As a result of Western hegemony, this discrimination continues to persist even to this day. However, Wynter wants to move towards a more inclusive understanding of man, supporting those that fall outside of the traditional understanding. OptiSolar takes Silvia Wynter’s philosophy of ‘Man - Genre of the Human’ into consideration, moving towards a more inclusive system for artificial intelligence, and society as a whole (Wynter 2003).

The key point of note is that it is not currently possible to eliminate all colonial influence from modern thinking. This is because society as a whole is entrenched in a Eurocentric mindset. Thus, the most reasonable decision when designing any form of system is to move further away from this mindset and closer to a more accepting worldview, as described by Sylvia Wynter.

OptiSolar recognizes that there may be inherent biases present within the systems being implemented, but tries to reduce their presence and impact to the best of its ability.

Design

OptiSolar is designed such that it minimizes the systems' ability to discriminate based on dataset and accessibility, aiming to move away from the discriminatory mindset prevalent in society. The dataset is taken from Google Cloud's SolarAPI, which provides historical data on weather patterns and rooftop data in recorded areas via satellite imagery. Thus, it is a more reliable source of information when compared to ground-level data collection (Belenguer 2022). This is because data biases, stemming from resources, technology, and prejudice at a location are less prevalent, provided that the satellite imagery presents its data fairly and accurately.

Additionally, the model is designed such that outliers do not hurt the resulting location evaluation. The model acknowledges the fact that there may be positive outliers, such as buildings that are significantly taller than others or those that are designed in an eco-friendly way, Thus, the scaling is not entirely linear, indicating that when a location is optimal for solar panels it receives a perfect, not affecting the existing threshold or any other values being evaluated. This provides the model with a way to be more standardized based on location, rather than being skewed by outlying data.

Development

The development process of OptiSolar follows the recommendations outlined in Nazer et al., by using a diverse training set, encapsulating many different forms of urban landscapes. This would include landscapes from across the globe, and of varying socioeconomic status. This way the overrepresentation of certain groups within the model can be minimized, which would skew its results towards those types of landscapes more common in the training set, such as developed western cities, excluding less developed areas on the outskirts of the city. The model then uses a color coded numeric scale displayed via the UI. This method allows for a greater understanding of the data and its intended meaning, increasing the transparency of the model for those unfamiliar with the system. The intent is to make the system more easily accessible to everyone.

Integration

OptiSolar's integration process revolves around the capability of communities to implement solar panels. It is readily apparent that there will be certain communities that do not readily have the infrastructure available to support the installation of solar panels and their required systems. Due to the nature of this issue, there is not a readily available solution, primarily due to socioeconomic limitations. However, OptiSolar's system still recognizes and evaluates locations based on its received data, not excluding locations due to their socioeconomic status.

Lifecycle

The project aims to reduce greenhouse gasses and alleviate the energy crisis, however, the successful application of solar energy does not only depend on technology, it is intricately linked to the decisions and actions of individuals, cities, and companies. What follows is an in-depth look at the possible interactions between individuals and the project, effectively deciding the lifecycle of the system.

Cognitive Perspective

It is common in society to believe that it is good to use renewable sources such as solar power instead of non-renewable sources to generate electricity, but there are still some factors that affect individuals to use solar power. Individuals may have personal habits or preferences that influence their decision to use renewable energy sources like solar power. For instance, some individuals may be more environmentally conscious and therefore more inclined to use renewable energy. Others may prefer traditional energy sources due to familiarity or perceived reliability. For corporations, the decision to use renewable energy can significantly impact their environmental image. Companies that utilize renewable energy sources like solar power can enhance their reputation as environmentally responsible businesses. This can attract customers who value sustainability, potentially leading to increased business. Policies and regulations can also play a crucial role. In some regions, policies may incentivize the use of renewable energy through tax credits or subsidies, making solar power a more attractive option. Conversely, in areas where such incentives are not available, individuals and businesses may be less likely to install solar panels. In addition, the cost of installation and the expected return on investment (ROI) can significantly impact the decision to install solar panels. If the cost is high and the ROI is low or slow, property owners may be less inclined to invest in solar power.

Decisions made in terms of individual, business, and city planning can have a profound impact on the data that API calls. For example, if the owner decides to modify the roof structure of the existing building, this change will directly affect the roof data, especially the shaded areas. For Google Solar API data, this change can lead to important changes in the solar potential data for the entire site. On the other hand, fluctuations in local electricity prices are also a key factor, as lower electricity prices reduce solar potential. This change will be reflected directly in the database, affecting the data returned by the API call. For example, falling electricity prices may have reduced the economic attractiveness of solar energy, affecting investment decisions and assessments of solar potential. In addition, building projects in urban planning are also an important consideration. When a construction company plans to build a new building in an area, the presence of this new building will directly change the topography and light conditions of the area, with a direct impact on the solar potential. This change needs to be reflected in the API data promptly to ensure that the system provides accurate and real-time information.

An individual's impact on the environment plays an important role in the use of solar energy. Assuming that residents in a certain area generally adopt solar power generation systems, this will directly reduce the demand for traditional energy, reduce carbon emissions, and promote the promotion of sustainable energy. However, if individuals lack awareness of the use of solar energy or adopt an environmentally unfriendly lifestyle, such as the heavy use of energy-intensive equipment without consideration for energy efficiency, this can slow the pace of the adoption of solar energy and limit its environmental benefits throughout the community. Therefore, individual choices and behaviors in solar energy use will play a key role in environmental sustainability, determining the actual impact of solar energy.

Through in-depth analysis of decision-making factors at the individual, corporate and urban planning levels, we can derive the diversity and complexity of decision making in this project. Viewing this through the lens of the cognitive architecture of ACT-R, decision-making involves the interplay of perceptual and procedural knowledge, reflecting the intricate cognitive processes individuals employ. The integration of ACT-R components—modules, buffers, and pattern matchers—plays a crucial role in understanding how these cognitive processes unfold. As Langley emphasizes in his article "Intelligent Behavior in Humans and Machines," (2021) the observation of human intelligent behavior provides important mechanisms and tasks that drive research. Individual environmental awareness, corporate environmental image, policies and regulations, and economic considerations together shape the practical application pattern of solar energy. The successful implementation of the project therefore needs to be fully understood and integrated into decision-making at the individual, corporate, and urban planning levels, as Langley points out, to drive sustainable development of renewable energy, and artificial intelligence must reconnect with cognitive psychology to achieve its original goal of creating intelligent systems with the same breadth of capabilities as humans.

Conclusion

In the exploration of the Google Solar API for determining optimal solar panel installation locations, our research delved into the urgent need for sustainable energy solutions due to escalating environmental concerns. Focusing on urban landscapes and the high energy demand they contribute to, our project aimed to accelerate the identification of prime locations for solar capacity. Leveraging historical weather data and neural networks, OptiSolar was designed to predict solar potential, considering factors like economic viability and societal impact.

Looking back on our project, it turned out that leveraging the Google Solar API effectively provided reliable historical data on weather patterns and roof conditions, enhancing the credibility of our model. However, we acknowledge the potential bias inherent in the system and are committed to minimizing it. Further mitigating bias will be a priority in future iterations, for example, we should add more language options to the system than just English. In addition, ensuring that the system is easier to use for users unfamiliar with the technology and that results are more clearly communicated is an area that needs strengthening.

Future research endeavors should focus on expanding the diversity of the training dataset, encompassing a wide range of urban landscapes globally and varying socioeconomic statuses. This approach aims to reduce overrepresentation biases in the model, making it more inclusive and applicable to diverse scenarios. The integration aspect could be further explored to address challenges in communities lacking infrastructure for solar panel implementation, addressing socioeconomic limitations. Additionally, forging deeper connections with cognitive psychology, as emphasized by Langley, will enhance the understanding of decision-making factors influencing solar energy adoption.

In conclusion, our project signifies a crucial step towards fostering sustainable energy practices in urban environments. The integration of Google Solar API and the development of OptiSolar underscore our commitment to providing accessible, transparent, and inclusive solutions. As we navigate the complexities of decision-making at individual, corporate, and urban planning levels, we remain dedicated to driving the sustainable development of renewable energy. The future holds promising opportunities for refining our model and contributing significantly to the global shift towards clean and renewable energy sources.

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