# Watt’s the hold-up?

Assessing the effectiveness of installed rooftop PV in Bristol’s 2030 net zero target.

**A 1967-word research proposal**

**Area of interest**

Anthroprogenic emissions have increased concentrations of greenhouse gas in the atmosphere to a level where the climate of our planet is changing at an unprecedented rate (Calvin *et al.*, 2023). One important strategy to reduce the future impact of climate change is to transition global energy systems away from fossil fuels towards cleaner renewable energies. This transition will reduce CO2 emissions, reduce air pollution and improve energy security (Abel *et al.*, 2018). The need for energy security in the UK was highlighted by the Ukrainian invasion which plunged millions of UK households into energy poverty when gas prices rose (Sovacool *et al.*, 2023). Whilst the UK has increased the use of renewables in its energy mix, an antiquated pricing system has inflated the price of energy sold on the national grid to be the highest in Europe (Bolton, 2024). This marginal cost pricing sets the price of energy to the most expensive source in the system (usually gas) meaning any cost saving from installing increased renewable energy capacity is not passed down to the household (Bolton, 2024). Smaller scale renewable energy installations can mitigate some of this cost issue. Rooftop photovoltaic systems (PV) can be installed on homes, workplaces and public buildings to reduce the requirement for energy from the grid (‘Solar Panels: 7 Crucial Things Its Good To Know’, 2023). The City of Bristol has highlighted its intentions to install up to 350Mw of rooftop PV in order to meet its 2030 net zero target (Bristol One City, 2020), as a relatively easy to install and low-cost option for clean energy within the city.

As a result of human induced climate change, Bristol has experienced more heatwaves with temperatures high enough to decrease worker productivity, disrupt highways and increase health impacts on vulnerable people (*Bristol City Council*, no date). This has put increasing pressure on the city’s health and social care system with spikes in calls to the NHS, hospital admissions and deaths (*Bristol City Council*, no date). Additionally, the risk of flooding has increased as sea levels have risen with 1200 Bristol properties at risk in 2024 (*Bristol City Council*, no date). As the climate continues to warm the severity and frequency of extreme weather events will increase (Calvin *et al.*, 2023)

The UK’s government response to climate change is to decarbonise the energy grid by 2050, but in 2018 Bristol city council was the first city to declare a climate emergency and pledged to reach net zero by an earlier 2030 target (*Bristol City Council*, no date). In 2019, the Centre for Sustainable energy reported that this city target was possible, through several changes including the installation of rooftop PV across the city (Roberts, 2019). In 2020, the Bristol One City Strategy was released with the aim to maximise renewable energy generation in the city through 350 Mw of rooftop PV installation (Bristol One City, 2020). This plan included installations on school roofs and council housing. In December 2022 , the Bristol City Leap (2022) initiative was announced with £500 million to be spent on low carbon infrastrucutre, targeting 180 Mw of zero carbon energy generation by 2027. This report aims to assess the extent current installations of rooftop PV have in meeting the 2030 net zero target.

**Objectives**

Investigate the progress made towards the 2030 rooftop PV installation target, six years on from the city’s declaration of climate emergency:

* **Estimate the capacity of installed PV on the roofs of Bristol.**
* **Contextualise the capacity installed relative to targets.**
* **Identify building types furthest from meeting PV potential.**

**Literature review**

Studies investigating the potential of rooftop PV within Bristol have highlighted that up to 1 Gw or 50% of the cities energy consumption (as of 2016) could be provided by rooftop PV (Letcher and Britton, 2023). More conservative estimates are made by the CSE at 500 Mw (Roberts, 2019), with council initiatives aiming for between 180 Mw (Bristol City Leap, 2022) and 350 Mw (Bristol One City, 2020) of rooftop PV capacity by 2030. Hepworth (no date) found that the installation of rooftop PV in Bristol could contribute to a 19% decrease in the cities CO2 emissions by 2030. One estimate from the Bristol energy cooperative projects 30 Mw (‘Free solar PV - Bristol Energy Cooperative - community-owned renewables’, no date) of rooftop PV has already been installed in Bristol, but there is limited detail in how they got this figure. When this value is visualised against the targeted rates of installation it appears low for meeting targets. There is a database of installed rooftop PV panels but it is commercial and not publicly available (*Rooftop Solar Installation Database - geospatial-insight.com*, no date). Both of these estimations leave room for improvement through this study.

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Description automatically generated**

Figure 1: Projections of rooftop PV installed capacity.

Developments in machine learning when combined with remote sensing have been seen to improve the estimation of PV potential on a city scale over empirical coefficient and 3D modelling approaches (such as lidar) (Sun *et al.*, 2022). The machine learning approach offers the benefit of using freely accessible large scale data, which is less computationally demanding than lidar modelling (Gassar and Cha, 2021). Machine learning increases the speed, cost effectiveness and precision of calculating parameters associated with renewable energies (Avtar *et al.*, 2019; Sun *et al.*, 2022). The main issue with using satellite imagery is that building hight isn’t included, reducing the accuracy of solar iridescence calculations. For this project we are exploring capacity installed, relative to capacity targets so the energy output of the PV is not the main point of exploration. 3D modelling techniques have been used for useful findings such as Gooding *et al (*2013) who found using digital surface models and lidar that across UK cities the building stock was a large influence on the potential for rooftop PV installation. Cities like Bristol with large amounts of building stock with industrial flat roofs had lots of space to install rooftop PV. An example of the use of machine learning approaches is Castello *et al.* (2019) who used Convolutional Neural Networks to automatically detect rooftop solar panels in Switzerland. This method will be followed for this research.

## **Novelty of approach**

The novelty of this work is applying a new and effective methodology from Castello *et al. (*2019), to the city of Bristol. The deep learning methods should increase the accuracy of identifying solar panels on roofs when compared to alternative approaches. The current estimates for installed capacity have a lack of detail in how they got these results. The method will increase the detail of findings when applied to policy targets and be more available than other data. There is data concerning the level of rooftop installations but it is not publicly available (*Rooftop Solar Installation Database - geospatial-insight.com*, no date). There is potential for new techniques to be devised as previous literature calls for more work around the type of building PV are installed on(Sun *et al.*, 2022) as most studies simplify and group roofs by type e.g. flat or gabled.

**Methods**

Solar panels installed on roofs in Bristol will be identified through training a Convolutional Neural Network (CNN) on high resolution satellite images of the city. Once the size of PV surface area across the city is calculated, the installed capacity can be estimated by comparing to an average panel capacity value. This capacity can then be compared to targets in order to assess the effectiveness of the role out to date.

There are satellite images at a high spatial resolution of 0.7 m x 0.7 m from the QuickBird-2 satellite as well as 1 m x 1 m resolution from the IKONOS satellite (*Very High Spatial Resolution Satellite Imagery | RSLab*, no date) but these may not be freely available. In this case, Landsat 8 imagery could be used but its lower spatial resolution of 30m x 30m would be difficult to train a model on as the resolution is 30 m x20 m. Satellite imagery could be used in conjunction with the CEDA Features earth collection which has a dataset of all building outlines, which would reduce the need for semantic segmentation of roofs from the rest of the image.

The method used to identify PV on roofs will follow the work of Castello *et al.*, (2019) who have conducted a similar analysis using Swiss aerial imagery and estimated a 94% accuracy at predicting which pixels were solar panels (with a 80-20 train test split). They were able to detect the sizes of panels by pixel-wise image segmentation. Feature maps within RGB satellite image data are pooled where they are semantically similar. The U-net segmentation architecture is used which has two phases, down-sampling and up-sampling. Their image resolution was 0.25 m x 0.25 m is very high. At this level only 3% of roof areas are the panels, requiring cropping down to 250 by 250-pixel areas. It is a supervised learning-based approach so 700 images were manually labelled to be used as a sample. Balancing false positives and false negatives requires careful selection of optimal weights.

This method will require access to a computer with a GPU. If this isn’t possible an alternative approach will be needed. One potential approach could be to contact the MCS certification company who certify PV installations and get the data on how many homes in Bristol have been approved. This would need to be combined with commercial and city council data if the scheme is only used for residential homes. Non residential data can be found through the Bristol energy cooperative and Bristol city council who have installed 15.8 Mw of rooftop PV (Bristol Energy, 2024; Bristol City Council, No date).

Further analysis would include classifying building type in order to estimate how the roll out of rooftop PV compares across different land use e.g. residential, commercial and industrial within the city. This would be useful for identifying where policy interventions could be most effective in terms of capacity potential. This could follow the method of Webber (2024).

**Ethical Considerations**

The main ethical issue associated with this analysis is the potential for bias within the ML classification. If flawed conclusions were made based on these bias results, the work would be less effective for informing policy. A potential source for bias could be caused by the ML technique being worse at identifying roofs which are cleaned of vegetation irregularity. Roofs with moss or vegetation growing may not be identified, thus decreasing the roof areas assessed for PV potential. Buildings where owners can’t afford to regularly clear the roof are likely to be of lower income. Minimising injustices within the PV installation system is important as generally rooftop PV uptake has been from higher income, homeowners. This raises issues of social injustice as homeowners are subsidized to get cheaper bills while renters receive no opportunity for discount. This is worsened by the lower potential for energy production from larger houses which are often shaded by trees, rather than the larger potential of flat roofs on tower blocks. It is unlikely for privacy to be violated from the satellite imagery as the resolution is not high enough for a person to be identifiable.

**Implications**

This project aims to identify the extent to which rooftop PV installation targets are being met. The use of a machine learning approach combined with remote sensing imagery will increase the accuracy of current progress predictions. Identifying the type of building furthest from meeting these targets will allow for policy to be adjusted to be as effective as possible. Improved knowledge on the progress the city is making towards net zero targets will increase visibility and help cater policy to reach the goals.

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