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PV, or not PV

PV, or not PV: using backcasting to explore policy, market and governance implications of local decarbonisation pathways such as urban PV

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Abstract

Since 2018, over three quarters of UK local governments have signed climate emergency declarations signalling a new phase in local climate action. Many areas are developing climate action plans and considering what policies could be adopted to increase the use of distributed energy resources, such as building-integrated photo-voltaic (PV) generation. In this paper we demonstrate how city-scale backcasting can be used as a tool to go beyond technical feasibility and explore the policy, market and governance implications of decarbonisation pathways across the local and nation scales. Using urban PV as an example we model three scenarios for increasing installed capacity in the UK city of Bristol and demonstrate how, in each case, PV switches from being a minor 'negative load' on the energy system to being the dominant factor determining the volatility and predictability of the energy demand during daylight hours. Current approaches to integrating distributed energy resources into the wider system tend to focus on predictive modelling and half-hourly pricing to drive demand-side response. Our analysis indicates the risks of relying on these non-real time methods and suggests that more granular techniques such as triggering local DSR based on changes in electricity system frequency could better manage the variability of high levels of PV deployment at the local scale. We also demonstrate the importance of developing new local approaches to system integration that bring together network operators, local authorities and other local actors to deploy renewable generation and flexibility assets in coordination.

Keywords: backcasting, PV, DSR, governance, network stability.

1.0 Introduction

1.1 Local government response to the climate emergency

Since 2018 almost three-quarters of district, county, unitary and metropolitan councils in the UK have declared a climate emergency (ClimateEmergency.UK, 2021). In almost nine out of ten (89%) cases declarations have been followed by climate action plans, and in over two-thirds (69%) a public commitment or aim to reduce emissions (Harvey-Scholes, 2019). Notably, in almost all of these authorities the goal is to achieve net zero emissions or close to it, and many have committed to achieving this by 2030 – two decades ahead of the target for the UK as a whole set by the Government (UK Government, 2019).

Political declarations of a climate emergency undoubtedly change the backdrop for policy makers and practitioners. They may create headroom for policy innovation and the allocation of additional staff and financial resources in some authorities. However, they follow a decade in which central government funding to English local government was almost

halved (Eckersley and Tobin, 2019), and as a consequence many local councils reduced resources allotted to sustainable energy, and climate change, resulting in a significant and in some cases complete loss of relevant skills and expertise.

The ambition and pace of the commitments underlying these new declarations goes far beyond what could be achieved by simply scaling-up previous actions and interventions (Roberts *et al.*, 2019). Furthermore, local government has a variable track-record of strategic energy planning and delivering effective energy policy interventions (Bale *et al.*, 2012) and (Hughes *et al.*, 2018). The imperative for swift and decisive action coupled with a lack of local expertise or national guidance makes capture by vested interests a risk, particularly from agencies seeking to preserve infrastructure and capital assets. There is also the potential for path dependency and what Carmichael describes as 'presentism'; focusing on single policy objectives to the exclusion of impacts and externalities (Carmichael, 2019). Previously, these have been balanced by a well-established, lengthy and consultative process for preparing local plans, taking on-average seven years to complete (*Ministry of Housing, Communities and Local Government*, 2020). However, if the intention is to decarbonise local energy systems within a decade, there will be a requirement for policy interventions that can be implemented almost immediately. Thus, local authorities require tools that will increase their understanding of potential policy interventions and the chances of quick and successful implementation, and of the implications should these be fully realized. To minimize the risk of squandering limited time and resources, they also need to understand which policies are likely to be ineffective or lead to unforeseen, unintended or damaging consequences. Here we propose the use of energy backcasting in combination with a simplified 'ball-park' model as a tool for analyzing potential policy measures and interventions.

1.2 Applying backcasting to the analysis of local decarbonization policy interventions

Backcasting, unlike forecasting and scenario modeling, focuses on the policies and measures required to achieve a specific and predefined energy future. As such it lends itself to a context where the overall objective and the timeframe are defined, in this case carbon neutrality within ten to fifteen years. Since Lovins (1976) outlined the principles of backwards looking energy analysis in the aftermath of the 1973-4 oil shock, these have been developed by scholars and practitioners as a conceptual framework, methodology and engagement tool for the analysis of whole energy systems and as an aid to understanding systemic changes necessary to achieve specific energy and climate related objectives. Here we apply the principles of backcasting within a narrowly defined framework to consider the implications of a specific policy intervention; in this case the deployment of roof-mounted photo-voltaic generation at scale within urban and semi-urban areas. We consider this to be one of a number of likely policy interventions advanced by municipalities seeking deep and rapid emission reductions. We combine backcasting with a simplified numerical model and consider the impact of increasing the deployment of PV in the city Bristol from $14.6MW_{peak}$ in 2016 to $366MW_{peak}$, $738MW_{peak}$ and $1GW_{peak}$.

Bristol is the largest city in South West England. It has an oceanic climate and receives approximately 1660 hours of sunshine annually ('Filton (South Gloucestershire) UK climate averages - Met Office', n.d.). It was chosen as a case study for its regional significance in terms of its size, and national significance in terms of municipal engagement on climate change. With a population of 472,400[1], and population density is similar to that of outer London, currently, it is the fastest growing of the Core Cities[2] UK ('corecities.com', n.d.). Average earnings are marginally (3%) higher than the average for Great Britain, though 41 areas are in the 10% most deprived in England, and 3 in the 1% most deprived (City Council, 2022). Since 2018 the City Council has been active in its response to climate change and in November that year

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[1] 2021.
[2] Belfast, Birmingham, Bristol, Cardiff, Glasgow, Leeds, Liverpool, Manchester, Newcastle, Nottingham and Sheffield.

passed a resolution declaring a climate emergency and subsequently established a cross-sector Environment Board ('Environment Board - Bristol One City', n.d.) which published a One City Climate Strategy ('Bristol One City Climate Strategy A strategy for a carbon neutral, climate resilient Bristol by 2030 Climate One City Strategy', n.d.) for making the city carbon neutral and climate resilient by 2030 with targets for solar PV generation within the city.

In this paper we show that without curtailment fully utilizing the output from $1GW_{peak}$ of PV capacity would meet almost of half the annual electricity demand in Bristol (based on 2016 demand data). However, at each of the capacity levels modelled, PV shifts from being a minor source of electricity supply or 'negative load', to a major cause of network volatility. The slew rate (defined here as the rate at which electricity demand increases or decreases) as well as the daily pattern and predictability of electricity demand in the city change significantly and become less predictable. This has implications for system stability and balancing. At the highest level of deployment (1GW) the slew rate increases by almost a factor of 10.

The technical challenges of integrating high levels of variable renewables in power systems are already well established (Bell and Gill, 2018; Pownall *et al.*, 2021; Rae *et al.*, 2020). In line with much of the emerging literature in this space we suggest that the impacts on network volatility of high penetrations of PV are likely to be resolvable through measures such as demand side response (DSR), and deployment of dispatchable electricity demand and supply such as static battery storage and the storage capacity in electric vehicles, provided these are bi-directional. However, our backcasting analysis reveals that, to realize what could be significant benefits of far higher levels of PV generation in urban areas, mitigating measures will need to be developed in parallel, with efforts to scale-up installed capacity. We argue this will require policy makers to take a broader perspective such that the expansion of renewable electricity generation is not treated in isolation. It also suggests a need for closer collaboration and strategic planning with Distribution Network Operators (DNOs). Finally, we suggest that energy retailers may have a role to play in helping to realize the benefits and mitigate the risks from increased PV generation. This may require a move away from Demand Side Response (DSR) interventions based on predictive half-hourly energy pricing to the use of real-time monitoring of system behaviour to trigger responses, and would have implications for the governance and regulation of the energy market.

Though we start from the perspective of local government, our findings also indicate the importance of reforming electricity markets to integrate an increasing proportion of variable (renewable) power, provide the required level of flexibility, and provide 'locational signals' such that flexibility and generation assets are developed in appropriate locations. To date, much discussion about market reform , system balancing and flexibility, including in Great Britain[3] (*Review of Electricity Market Arrangements Consultation Document*, 2022), has assumed that distribution-level balancing can be achieved with a granularity of no-less -than thirty-minutes (i.e. half-hourly settlements). As discussed, our findings suggest that as the proportion of variable, distribution-level renewable generation increases, this may not be easily achievable or desirable, and that the location of renewable electricity generation is significant and should also be taken into account. Thus, we demonstrate the limitations of non-locational approaches to managing system stability and balancing driven by half-hourly pricing, and we provide new insights into the implications for multi-scalar governance of energy system change.

These findings should be relevant to those tasked with reforming the GB energy market and defining the role of the wholesale and distribution-level components within it. They should also be applicable to Distribution Network Operators (DNOs), as they transition to Distribution System Operators (DSOs), given their current and developing role in distribution system management and system balancing.

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[3] For example UK Government 2022 consultation 'Review of Electricity Market Arrangements'.

The remainder of this paper is structured as follows; Section 2 considers the role of backcasting as a tool for policy analysis and development, and Section 3 the application of backcasting to PV development. Section 4 sets out the methodology employed here, and Section 5 our results. Conclusions and policy implications are presented in Section 6.

2.0 Backcasting as tool for policy analysis and development

Scholars and practitioners have developed backcasting as a conceptual framework and a tool for policy analysis since the mid 1970's. More recently backcasting has been used as a tool for sustainable city planning (Phdungsilp, 2011a) city-scale carbon management (Bailey *et al.*, 2011) and as a participatory tool for strategic planning of heating (Pereverza *et al.*, 2019a). Here, we apply backcasting also at a city-scale, but in a more targeted way with the objective of producing a novel, spatially-granular dataset to inform our understanding of the system impacts of increasing the capacity of urban PV, in response to local policy drivers.

Backcasting has been described as '*generating a desirable future, and then looking backwards from that future to the present in order to strategize and to plan how it could be achieved*' (Vergragt and Quist, 2011a, p. 747) (Quist and Vergragt, 2006). It emerged in the 1970's from the field of future studies, known as normative forecasting and normative futures studies (Vergragt and Quist, 2011a), since when scholars and practitioners have developed backcasting as a conceptual framework, methodology, and tool for participatory engagement. As well as being applied to the analysis of sustainable energy systems it has been used to consider broader societal needs including housing, food, transportation and chemicals (Vergragt, 2005).

Backcasting arose in the aftermath of the 1973-74 oil price shock from discontent with the planning of energy systems in the UK and USA on the basis of energy forecasts, the extrapolation of what Lovins (1976) described as the 'recent path', and a concern that this was leading to unconstrained expansion of the energy system. As an alternative he proposed that energy analysis should look backwards from a defined and desirable energy future. He also proposed soft energy paths as alternative routes to these more desirable, and defined futures. These would be based on policies intended to reduce demand and conserve energy, and generate energy renewably as an alternative to fossil fuels (Robinson, J. B., 1982).

The use of scenarios to map-out and shape strategies and pathways to the future is long-established and may be considered in terms of what *will* happen, what *could* happen and what *should* happen (Linstone, 1999) (Börjeson *et al.*, 2006) (Vergragt and Quist, 2011b). Backcasting is explicitly subjective in that the end point, objective or goal is pre-defined, and so is concerned with the question what *should* happen?

Early work on backcasting centered on the USA (Lovins), Canada (Robinson) and Sweden (Lönnroth *et al.*, 1980) (Vergragt and Quist, 2011a). As described by Bibri (2020), concern about ecological disruption and interest in alternative energy futures since the 1980's lead to considerable work in Sweden on the development of backcasting for sustainability, (Dreborg, 1996a), (Holmberg, 1998) (Holmberg and Robert, 2000), (Höjer and Mattsson, 2000). More recently the study of backcasting has expanded in scope and geography to address sustainable transport, (Akerman *et al.*, 2000), (Åkerman and Höjer, 2006), emissions (Höjer *et al.*, 2011), (Svenfelt *et al.*, 2011), industrial transformation (Quist and Vergragt, 2003), resilient energy futures (Kishita *et al.*, 2017), and the development of system-wide energy policy (Sharmina, 2017), (Emodi *et al.*, 2019).

In the UK, the government has used both backcasting (Royal Commission on Environmental Pollution, 2000), and prospective energy scenarios (Rothman, 2007) in the formulation of national policy objectives.

The subjective nature of backcasting, raises questions about who should define relevant goals and end points, and in the 1990's led to work on participatory backcasting. This has been applied to regional and local planning, climate policy,

hydrogen and households (Vergragt and Quist, 2011a) and subsequently sustainability and cutting energy use in buildings (Robinson, John *et al.*, 2011), (Eames and Egmose, 2011), (Svenfelt *et al.*, 2011). Such is the diversity of approaches to this that Wangel proposed a system for categorizing participatory backcasting (Wangel, 2011).

Scholars differ on whether backcasting is a method or general approach. Dreborg argues that it is a multidisciplinary approach that being orientated to solving long-term problems, should be regarded as applied science, (Dreborg, 1996b). Robinson maintains it is a method, having systemized Lovins initial work into a six-step methodology (Robinson, J. B., 1982) (Robinson, J., 2003) that could be applied to the analysis of transformation in energy systems:

    i)   Specify goals and constraints,

    ii)   Describe current energy consumption and production,

    iii)   Develop outline of future economy,

    iv)   Undertake demand analysis,

    v)   Undertake supply analysis,

    vi)   Determine Implications of the analysis.

Anderson (Anderson, 2001) developed Robinson's approach, and proposed a method to address what he identifies as shortcomings in Robinson's methodology. These are the reliance on long-term economic predictions required in step three and need to construct of an 'end-point economy', which Robinson (Robinson, J. B., 1982) regards as 30 to 50 years in the future, and the inclusion of projected energy costs, embedded within the consumption profiles for the future-economy model. Anderson has set out a five-step methodology which includes an explicit acknowledgement of what he regards as the sub-optimality of backcasting analysis, and the exclusion of long-term energy forecasts, thereby addressing the shortcomings in Robinson's approach.

2.1 The pros and cons of backcasting versus forecasting when considering complex systems

Within the scope of this article, we regard the subjective nature of backcasting is a 'pro'. It allows a specific end-point to be defined and evaluated at a granular level, whilst screening-out system complexities. By contrast, forecasting the outcomes of a policy intervention applied to a complex system such as a city, requires evaluation of a large number of variables and high degree of uncertainty. This process tends to produce divergent scenarios and subdue outcomes, making the need for more detailed analysis less apparent. As forecasts must account for dominant trends, they are also unlikely to produce solutions at odds with those trends (Phdungsilp, 2011b).

The divergent nature of forecasts is demonstrated in the annual distribution level forecasts produced by the DNO Western Power Distribution (Haynes and Millman, n.d.). Combining National Grid ESO Future Energy Scenarios with local planning authorities' development forecasts, and outputs from stakeholder engagement, this comprises four Distribution Future Energy Scenarios (DFES) for the near-term (2021-2027), medium-term (2027-2035) and long-term (2035-2050). Under two of the (2021) DFES scenarios, 'Consumer Transformation' and 'Leading the Way' just over 1GWpeak of small-scale PV[4] is projected by 2030, so similar to the upper estimate considered here. However, this applies to the whole of the South West (England) Licence area rather than Bristol, masking the potential consequences of high levels of PV in a specific urban area. The divergent and non-specific nature of these forecasts is exacerbated, in this instance, by a lack of geographical supply point data.

Unlike forecasts energy backcasting is inherently subjective, and this limitation needs to be considered when evaluating outcomes, particularly when it is deployed as an energy system planning tool. Making backcasting participatory

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[4] Small-scale: defined as less than 1MWpeak capacity.

(Pereverza *et al.*, 2019b) and combining backcasting and explorative scenario development (Kok *et al.*, 2011), are among the options that have been proposed to address this. Here, we employ backcasting more narrowly with the objective of understanding at a granular level, the consequences of a specific policy intervention.

3.0 Applying backcasting to PV deployment

3.1 The selection of PV as a potential policy intervention

There are multiple policy interventions and measures to which a backcasting approach could be applied. In this case we have selected PV, for the following reasons:

i)   *Previous experience of policies requiring renewable energy in the built environment.* A number of local planning authorities in the UK have experience of PV either on their own buildings or as planning requirement for new development. In Bristol, the adopted planning policy (Bristol City Council, 2011) requires developers to reduce residual CO_2 emissions in new residential and non-residential buildings by 20% through on-site renewable energy generation, and commonly developers have opted to meet this through the installation of roof-mounted PV.

ii) *The falling cost of PV*. In Europe the cost of crystalline solar PV modules declined between 88% and 95% from December 2009 and December 2021, depending on the type, (Renewable Energy Agency, 2022) In the UK between 2014/15 and 2018/19 the mean cost of small installations (0 – 4kWp) reduced by 12.3% (BEIS, 2020) and some analysts believe that prices will continue to reduce as a result of an increase in global manufacturing capacity and technical innovations such as thinner wafers, and improvements in the energy efficiency of the manufacturing process (Bloomberg New Energy Finance, 2017).

iii) *Location*. Mounting PV on existing buildings places energy supply close to demand thereby reducing the energy losses and the financial cost of transmission.

iv) *The availability of land as a counterfactual to using existing roof space*. In Great Britain average power density and average primary energy consumption per unit area of land are similar. (MacKay, D. J. C., 2013), so maintaining British energy consumption renewably would require an area of land similar to that of Great Britain. MacKay also notes the similarity in the power density of different forms of renewable power generation, meaning that not utilizing available urban roof space to generate renewable power would require an equivalent land area elsewhere.

v)   *Roof-mounted PV is already being proposed as a measure for achieving net zero emissions*. The scaling-up of PV capacity is already being considered as a measure that will be required to achieve net zero emissions. In Bristol it has been recommended that to achieve net zero emissions (Roberts *et al.*, 2019) every other roof will require PV, from one in forty-eight currently.

Thus, it is likely that local authorities will consider the installation of high levels of PV capacity as part of their response to achieving local emission reductions.

3.2 Technical analysis of the regional and local implications for electrical distribution networks from increased levels of PV deployment

Work by scholars and practitioners on the localized and regional impacts of the high levels of installed PV provides a good understanding of the impacts on grid stability (such as (Shah *et al.*, 2015)(Haque and Wolfs, 2016)(Sanders *et*

al., 2016), and the role of mitigation measures such as energy storage. Whilst undoubtedly of benefit to electrical and system engineers this work is likely to be less useful to policy makers in deciding whether and how to accelerate the installation of PV in urban areas.

The picture is complicated further by the inherent variability in the output from solar PV systems. This is determined by the apparent motion of the sun in the sky (which is entirely predictable), and the movement of weather systems including the local formation, distribution and motion of clouds, which is less predictable. Thus, the power output and energy system impacts from a large distributed PV system are related to the installed capacity in a given location, and the distribution of PV resource relative to the direction of prevailing weather systems. This is particularly significant when considering high levels of installed capacity over a large area such as a city (Perez *et al.*, 2016), (Marcos *et al.*, 2012), (Murata *et al.*, 2009), (Woyte *et al.*, 2007), and (Wiemken *et al.*, 2001). The density (peak capacity per unit area) of the installed PV capacity adds a further variable (Perez *et al.*, 2016). A $1MW_{peak}$ system installed at single location will experience greater variability and intermittency as consequence of the progressive variation in cloud cover, than a system of the same capacity distributed across a region or country.

These impacts pose a dilemma for policy makers; whether to ignore them on the assumption that in-time they will be addressed by technical means such as more sophisticated predictive modeling of local weather systems and energy storage, or whether to try and design policies that preempt them, for example by incentivizing the placement of PV in certain locations. The first of these risks unintended consequences that may reduce or negate the overall benefits, or be costly to mitigate. The second implies a level of policy precision that we suggest is unlikely to be achievable in practice in the UK. A more viable and practical solution, particularly in light of the very short time horizons being proposed for cutting emissions, may be to develop an understanding of the likely impacts and interactions now, such that (assuming there is a net benefit) the accelerated delivery of PV can commence while developing complementary solutions and mitigation measures as installed capacity increases.

The remainder of this paper uses a simplified backcasting and ball-park model to consider the implications of significantly increasing the installation of PV, at three levels, within an urban conurbation (Bristol).

4.0 Methodology

The methodology falls into four parts:

- Model half-hourly electricity demand in Bristol for 2016.

- Simulate and model the output from three levels of installed PV capacity, $366MW_{peak}$, $738MW_{peak}$ and $1GW_{peak}$ for 2016 (referred to as 'PV arrays' below).

- Combine the estimated electricity demand with the simulated output from the three PV arrays.

- Analyze the results for policy, market and regulatory implications.

Temporal electricity demand data for Bristol was not available from National Grid or Ofgem. Generating an empirical, bottom-up demand profile for Bristol was outside the scope of this research, so the national demand profile from the National Grid IO14_ND national dataset was scaled pro-rata, by population. This was used to estimate half-hourly demand for 2016 (the most recent year for which all the required data was available). The absence of a regional or Bristol demand profile is a significant data gap, and providing granular data at this scale would be of benefit to practitioners and scholars working on the decarbonization of the distribution system. Extrapolating a national demand profile will by definition smooth-out local variations in demand such as those arising from high consumption industrial

and commercial users. However, given that the IO14_ND dataset is based on actual consumption, and that the data has been adjusted to the population of Bristol (454,200 people[5]), and the simplified nature of the numerical model used here, we consider it to be appropriate for the purposes of this research.

Of the three levels of peak PV capacity modelled, the lower and mid, 366MW$_{peak}$, 738MW$_{peak}$, were derived from the outputs of a Government funded study 'Bristol Sunshine – An Analysis of Solar Rooftop Mapping Techniques and outputs' (Highman, 2011). This used an aerial LiDaR survey to assess the potential for roof-mounted PV in the city. The upper level of 1GW$_{peak}$ was derived from a 2013 council backed initiative known as 'Bristol Solar City' ('Plans for solar powered Bristol described as "over ambitious"', 2013) to install 1GW of new capacity in the city by 2020.

The outputs from the three PV arrays were simulated using the EU PVGIS-CMSAF web-based application and dataset (European Commission, 2017) with the location set to Bristol and data logged in Excel. PVGIS generates an hourly, location specific estimate of the power output from a PV system taking account of geographical location and weather including cloud cover, orientation, tilt, system type (mono-crystalline, poly-crystalline etc) and inverter losses, all of which can be specified. Datasets produced by the PVGIS-CMSAF model are largely generated using data from geostationary satellites, supplemented by data from ground-stations and climate reanalysis. The latter entails computation of numerical weather forecasts with algorithms validated by comparing modelled outputs of previous time-periods with observations from ground-stations. More broadly, solar radiation data produced by the PVGIS-CMSAF model were validated by comparison with ground-station observations (Amillo *et al.*, 2014; Mueller, R. *et al.*, 2012; Mueller, R. W. *et al.*, 2009; Young *et al.*, 2021). The EU PVGIS model is updated and revalidated periodically to reflect changes in technology, solar radiation and climatological data. Analysis by Young et al (2021) shows an increase in irradiation and annual PV production of a few percentage points between modelled output datasets for the period 2005 to 2016, and datasets for the period 2017 to 2020; the latter having been generated using an updated model. Variations in the estimated irradiation (Wh/m^2) and the annual yield (kWh/annum) of a PV array may be of significance when considering the net contribution of a PV system to the annual energy demand of a building, group of buildings or a settlement. In terms of the policy and governance implications identified in this paper, a variation of a few percentage points between models is not significant as it is a fraction of the difference between the three peak capacities of PV system outputs considered here.

Hourly output from the PV arrays in 2016 was estimated assuming crystalline silicon PV modules with a peak output of 1kW and inverter losses of 14%. A multiplier was used to adjust the peak output to 366MW$_{peak}$, 738MW$_{peak}$ and 1GW$_{peak}$ respectively, having deducted an estimate of existing installed PV capacity in 2016. This was derived from sub-regional feed-in tariff installations for 2016 (Department for Business Energy and Industrial Strategy, 2016).

An allowance for the variation in roof orientation across the city was made by assuming that for each of the large-scale PV arrays, panels were divided into eleven segments of equal peak capacity, with orientations between due east (90 degrees) and due west (270 degrees) with the bearing of each segment 18 degrees apart. A tilt angle of 33 degrees from horizontal was assumed in all cases. The output from each portion was modelled separately, prior to summing the results to produce cumulative estimated hourly outputs for 2016.
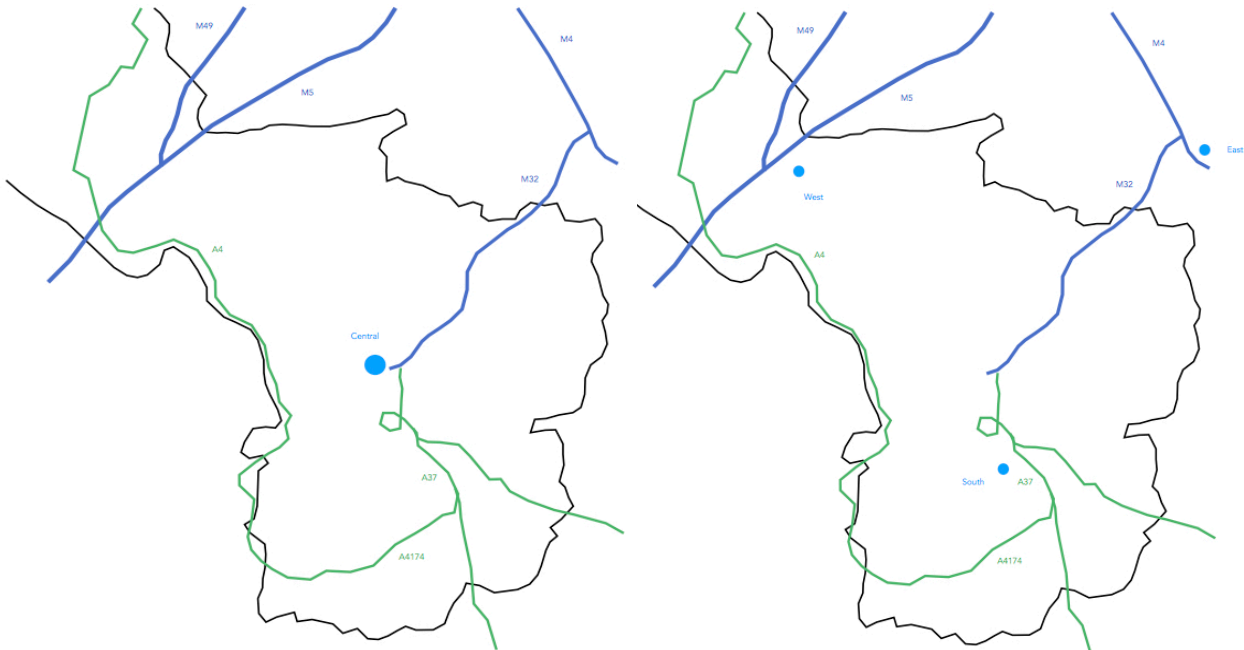
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[5] Population of Bristol in 2016.

Figure 1. Initial point location for modelling PV output (left), revised locations west, east and south shown on

In the first instance the output dataset was generated assuming that all the additional PV capacity was installed at a single geographical location, taken to be the centre of Bristol, and therefore that variations in irradiance due to temporal changes in cloud cover affected all parts of the array simultaneously. The resolution of the PVGIS model is 5km (confirmed by correspondence), so to estimate the effect of hourly changes in cloud cover, the model was rerun splitting the additional PV capacity into three equal parts, installed at three separate locations. This was repeated for each of the three levels of PV capacity modelled. The point locations of each portion of the array are shown Figure 1. The variation in the roof orientation within each third of the total array was incorporated into the model as above, and the other variables remained unchanged. The outputs for each portion were then combined to give total estimated hourly outputs for 2016.

The estimates of half-hourly energy demand data were averaged to estimate hourly electricity demand. This data was then synchronized with hourly power generation for the modelled system and outputs were graphed using MS Excel.

5.0 Results

Estimated hourly electricity demand and the estimated output of the PV system at the low, mid and peak capacities were plotted from 1st January to 31st December 2016. By way of illustration, graphs 1 to 4 show estimated electricity demand and estimated output from PV systems for one-week periods of in January, March, June and September 2016. Assuming no curtailment, the low, mid and peak capacity levels, generated 18%, 36%, and 49% of the total estimated annual energy demand in Bristol for 2016. As shown in graphs 1 to 4, the extent, frequency and duration of periods when supply exceeds demand varies during the course of the year with seasonal variation in irradiance. Electricity demand would need to be increased, or energy stored or exported to other parts of the distribution network to avoid curtailment during periods when supply exceeds demand.
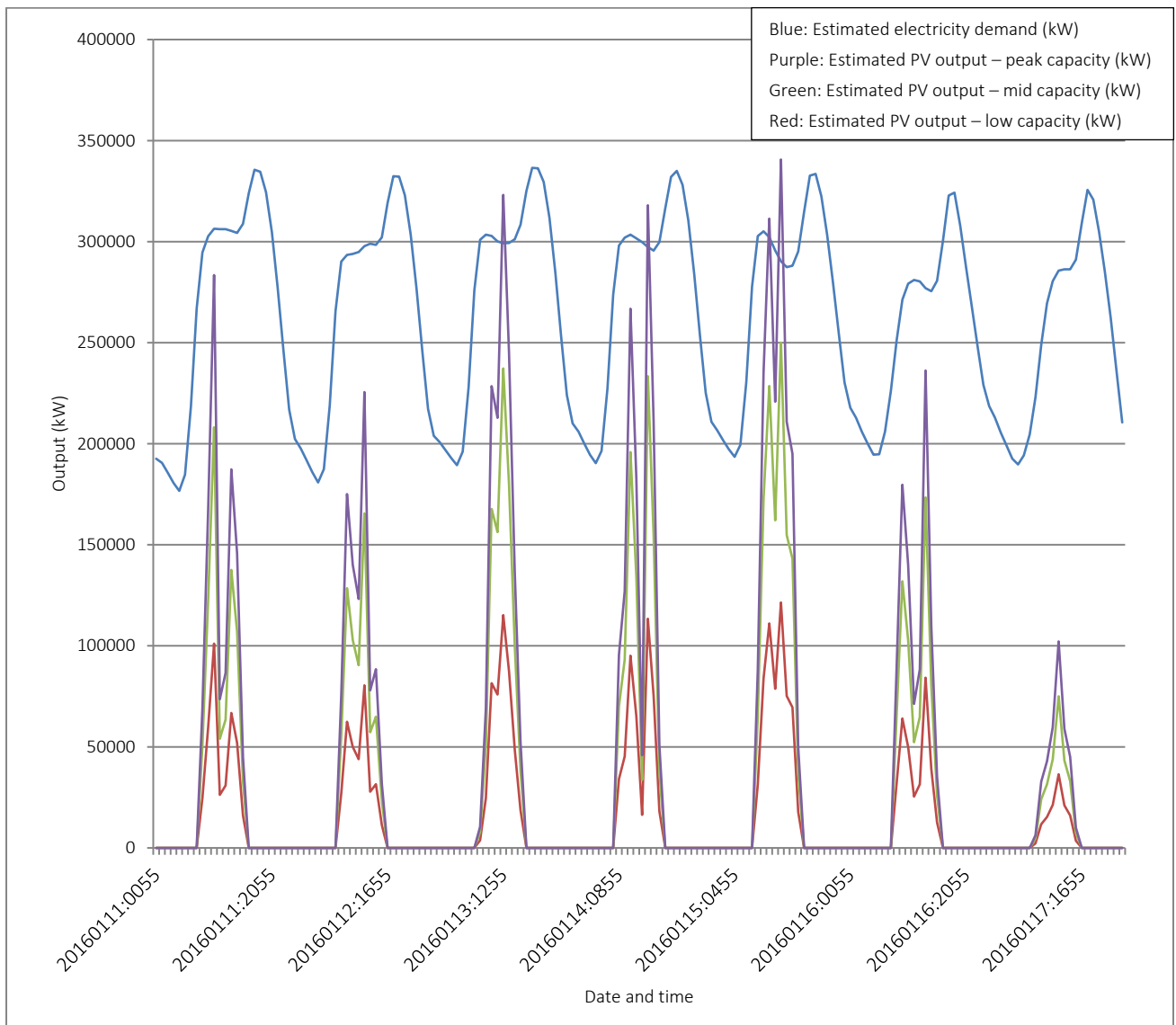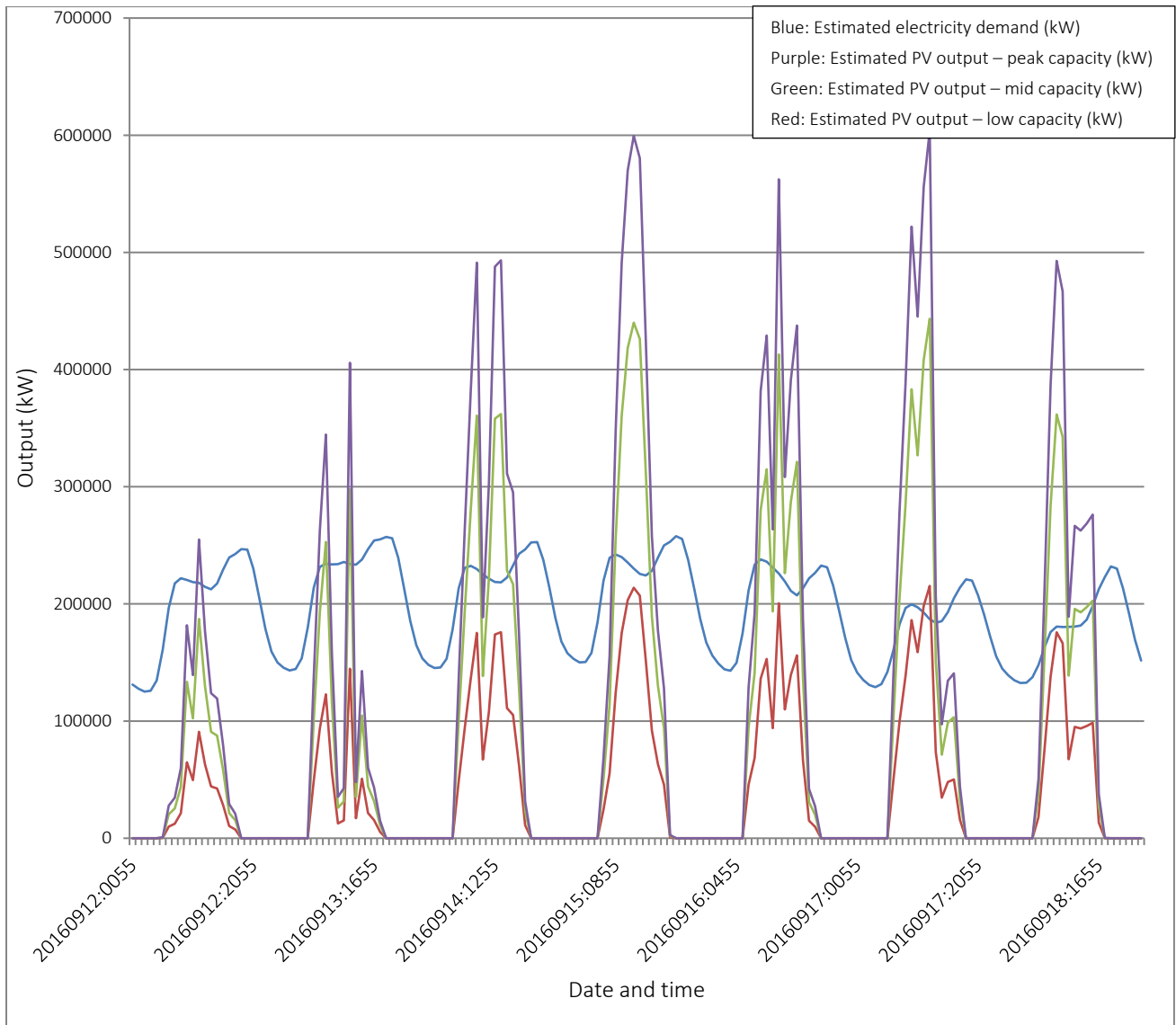
Graph 1 showing modelled electricity demand and supply for period 11-01-2016 to 17-01-2016. Estimated electricity demand (kW) (blue), and modelled output (kW) from PV arrays of low (red), mid (green), and peak (purple) capacities.
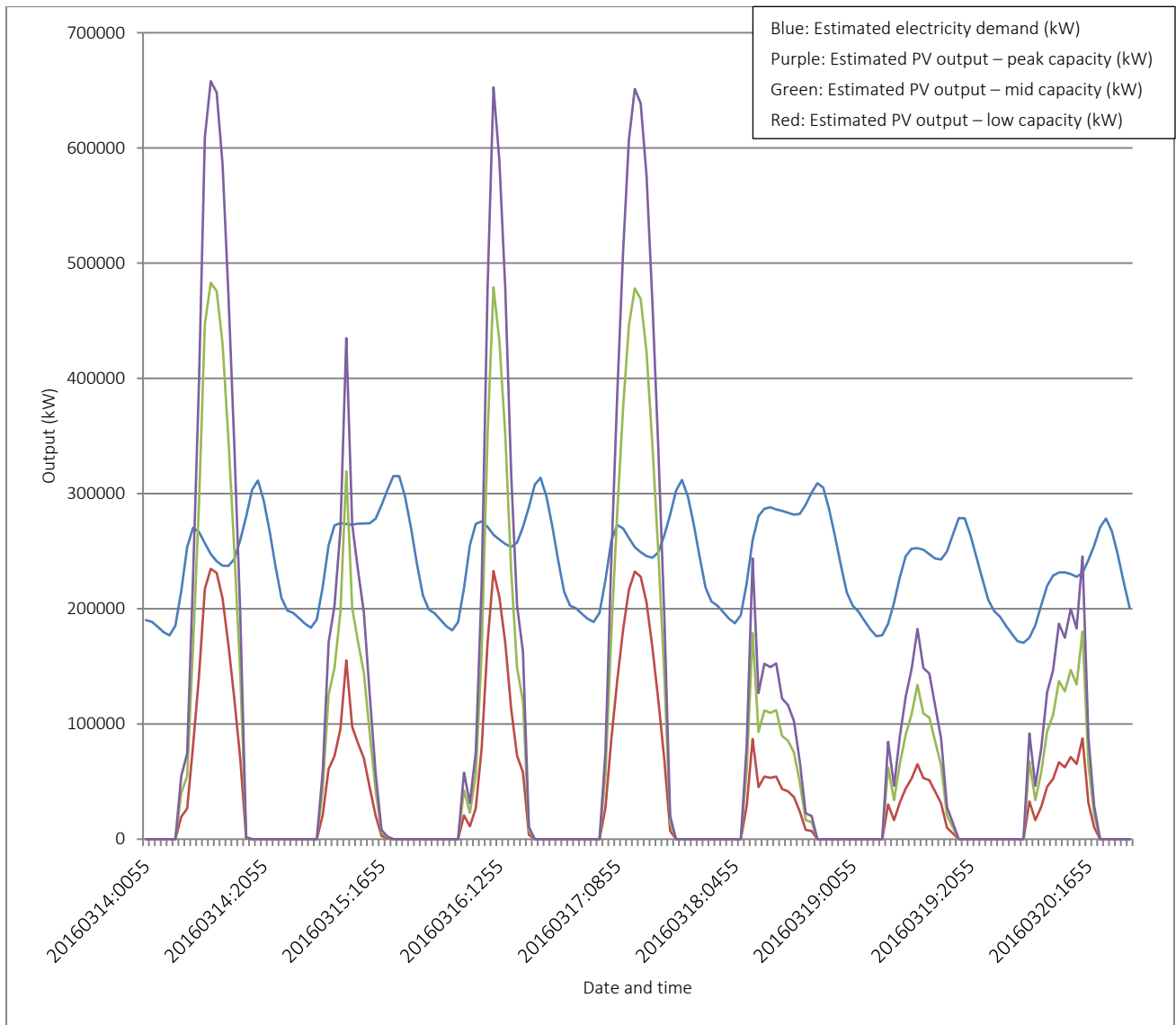
Graph 2 showing modelled electricity demand and supply for period 14-03-2016 to 20-03-2016. Estimated electricity demand (kW) (blue), and modelled output (kW) from PV arrays of low (red), mid (green), and peak (purple) capacities.
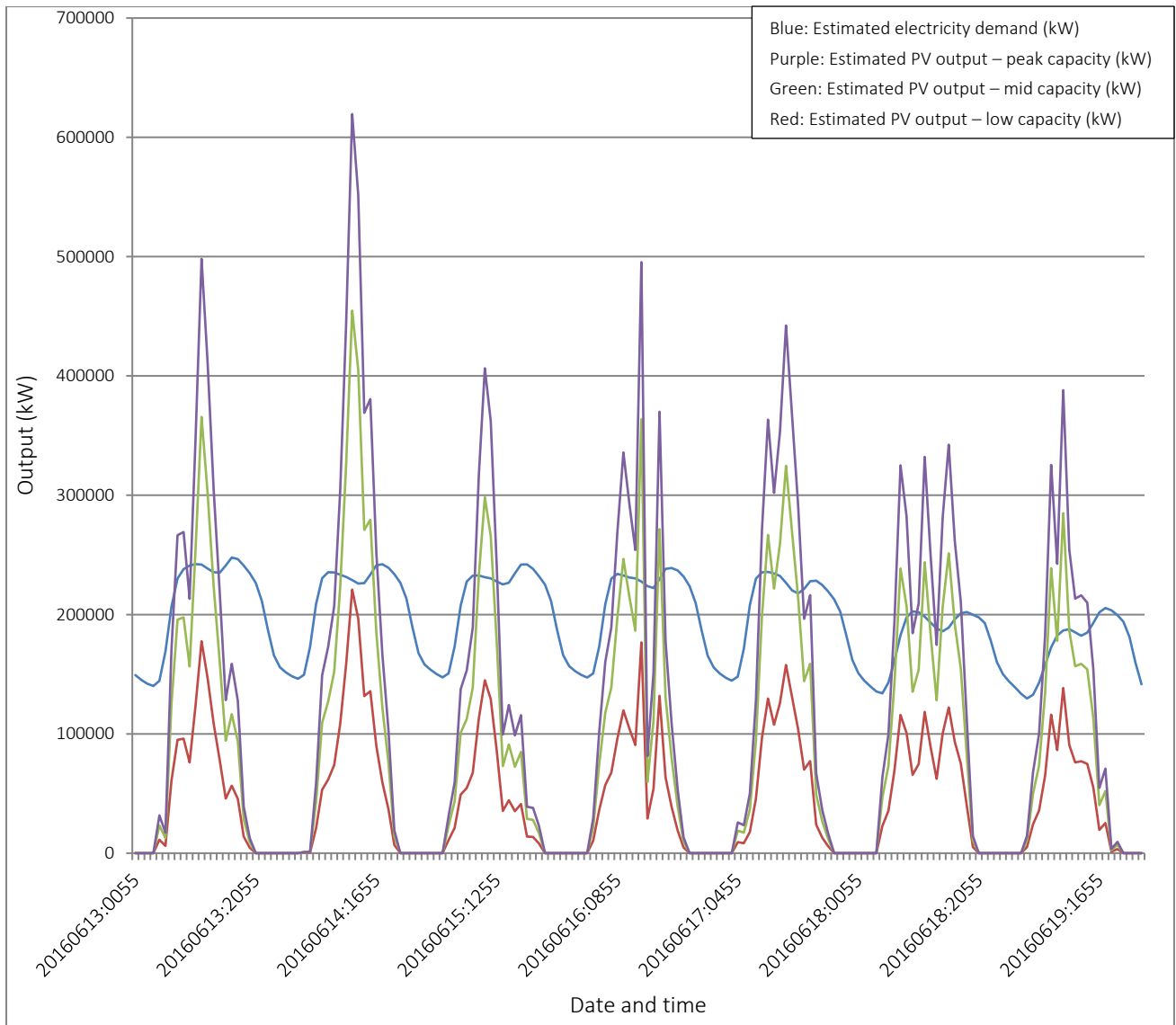
Graph 3 showing modelled electricity demand and supply for period 13-06-2016 to 19-06-2016. Estimated electricity demand (kW) (blue), and modelled output (kW) from PV arrays of low (red), mid (green), and peak (purple) capacities.

Graph 4 showing modelled electricity demand and supply for period 12-09-2016 to 18-09-2016. Estimated electricity demand (kW) (blue), and modelled output (kW) from PV arrays of low (red), mid (green), and peak (purple) capacities.
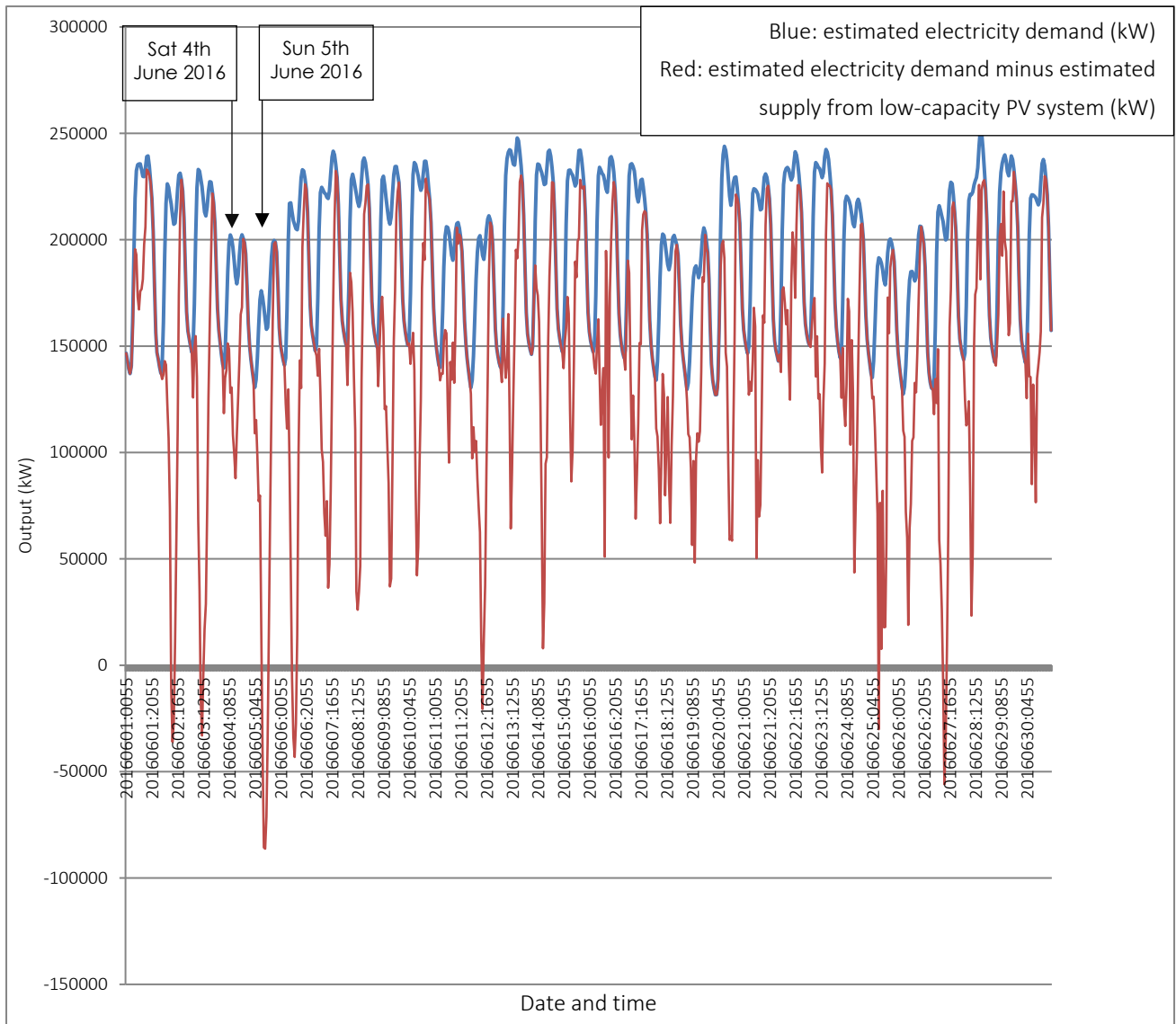
By subtracting estimated electricity output from estimated electricity demand the change in the profile of net demand, and the slew rate (rate of change) as a result of increasing PV capacity can be seen.

Graph 5 showing estimated electricity demand profile (kW) (blue) and estimated demand minus estimated supply (kW) based on low-capacity PV system (red) for 01-06-2016 to 30-06-2016. Negative values indicate periods when supply exceeds demand.

Several points can be inferred from Graph 5. There is considerable variation day-to-day in the PV output and the resultant net demand. On June 4th 2016 for example, the model shows a modest contribution from installed PV capacity which increases significantly the following day to the extent that supply exceeds demand, assisted by the weekend (Sunday) reduction in demand.

The model also shows the impact on net demand of significant and rapid variation in the output from the PV array due to changes in irradiance (from variations in cloud cover) across the whole array, as illustrated in the Graph 6.
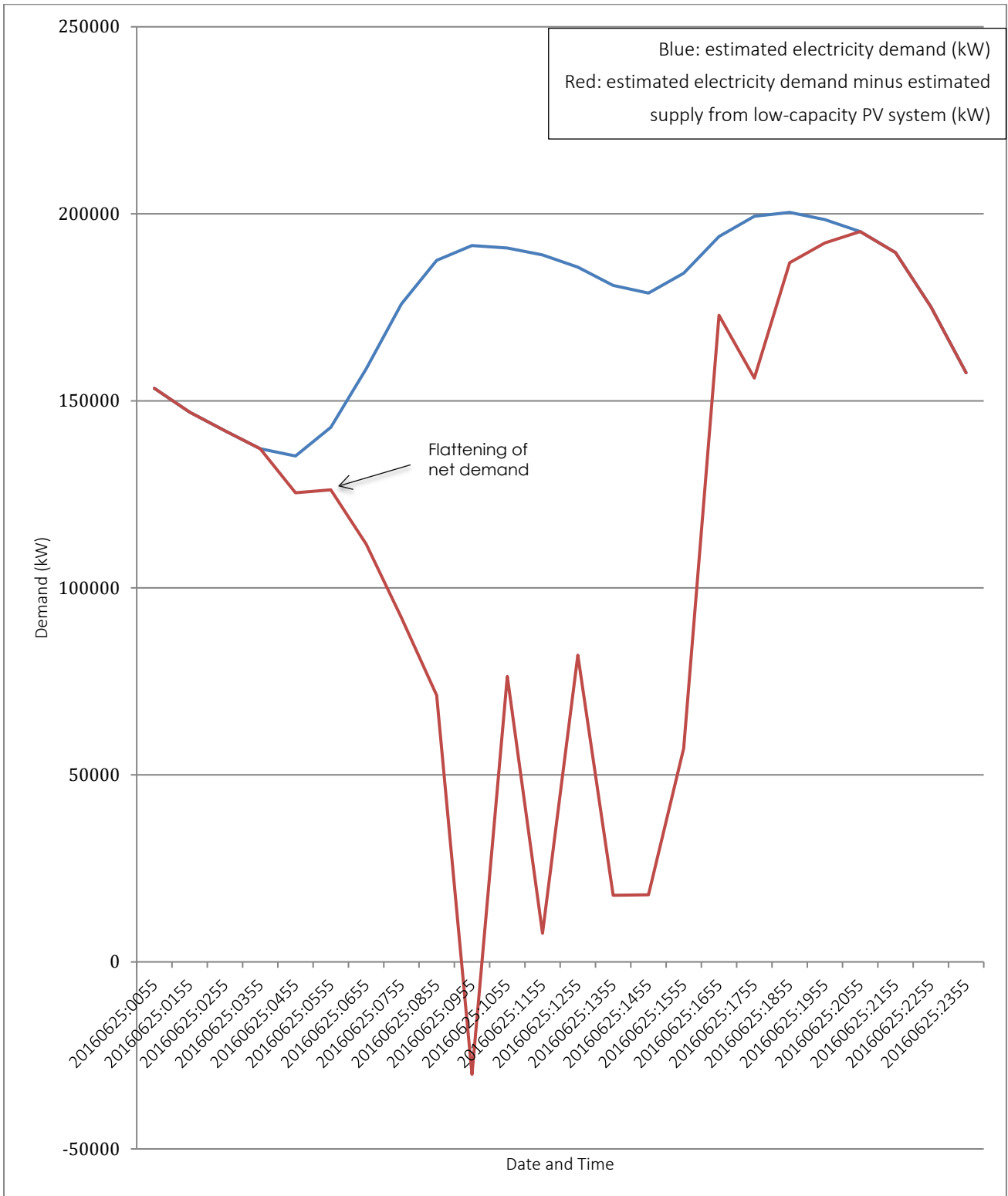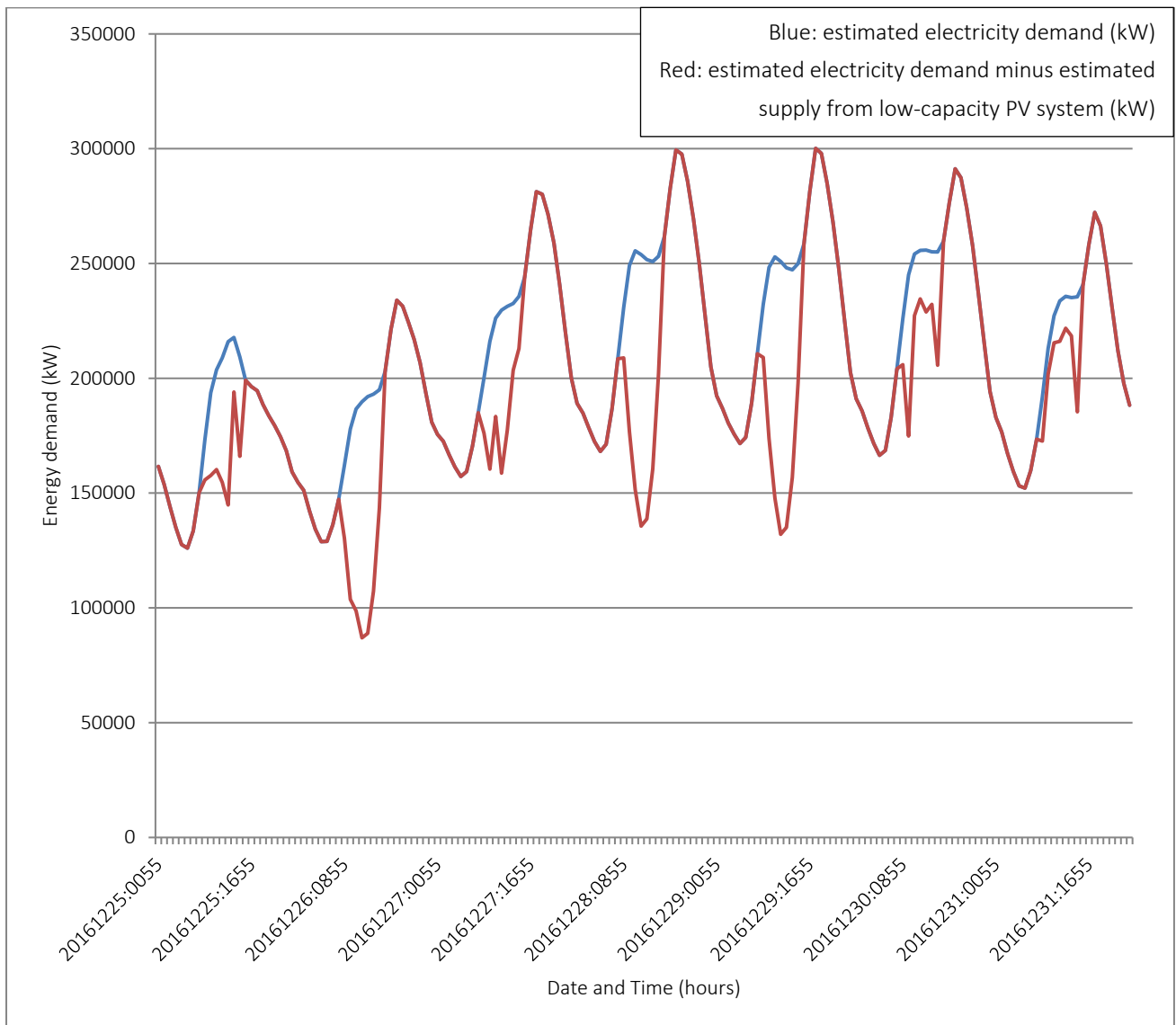
Graph 6 showing modelled electricity demand (kW) (blue) and net demand (kW) with low-capacity PV system (red) on 25th June 2016.

The change in net energy demand during daylight hours may be considered as the sum of two waves, electricity demand and the cumulative output from the PV array. The variability and change in the slew rate (rate of change) in net demand depends on how the phase and relative amplitude of each wave combine. Where demand and energy generation are both moving the same direction, i.e. increasing or decreasing, as would be the case on a clear summer morning, the effect can be to flatten the net demand, until the point where energy generated by the PV array exceeds demand (graph 6). This interaction can also produce a significant increase in the slew rate of net demand, and a rapid change in state from one where net demand is falling to one where it is increasing. This is the case for example when electricity demand is increasing and supply from the PV array rapidly reduces due to a reduction in irradiance as result of cloud cover. While in broad terms the seasonal variation in PV output is predictable, the hourly variation is dependent on local cloud cover. The ability to predict this is related to the scope and granularity of local weather forecasting.

The variability in net demand and the higher rate of change of net demand are key findings from this model, the implications of which are discussed below. Prior to the addition of new PV capacity in this model, the maximum rising slew rate in net demand in 2016 was modelled as just below 50MW per hour, and the maximum falling slew rate was just over 40MW per hour. The addition of 366kWp of PV capacity (the lowest capacity level modelled), increased the maximum rising slew rate 3 times to approximately 145MW/hr and the maximum downward slew rate to approximately 170MW/hr. For the largest $1GW_{peak}$ PV system modelled, the maximum rising and falling slew rates are nearly ten times greater than current values at 410MW/hr and 490MW/hr respectively.

The increased variability in net demand from the addition of PV is not confined to the summer months when the solar output will be highest. Graph 7 shows the modelled variation in net demand between 25th and 31st December 2016 for the smallest (366kWp) array. While supply never exceeds demand the PV produces significant variation in the net demand. A further observation from the modelled data is that the peak output from an array of a given size is significantly below the theoretical peak output. The peak outputs for the low ($366MW_p$), medium ($738MW_p$) and high ($1GW_p$) output systems were modelled as 277kW, 570kW, and 776kW.

Graph 7 showing modelled electricity demand (kW) (blue) and hourly variation in net electricity demand (kW) (red) following inclusion of low-capacity PV system for period 25-12-2016 to 31-12-2016.

6.0 Conclusions and policy implications

6.1 Discussion

In this paper we have used a simplified, 'ball-park' model to backcast from three specific end-points (PV capacity levels), with the intention of exploring the policy, market and governance implications of increasing PV in a city. This contrasts with previous analysis by scholars and practitioners of the local and regional effects of high levels of PV generation that has focused on the technical implications. Our model suggests that at the three levels of installed capacity considered, PV switches from being a minor 'negative load' on the energy system to being the dominant factor determining the volatility and predictability of the energy demand profile during daylight hours. It raises three potential issues relevant to policy makers: i) the discrepancy between peak output derived from the specified peak capacity of PV panels, and the modelled peak output of an *installed* system. ii) A need for dispatchable demand to avoid curtailment when electricity supply

exceeds demand and iii) the potential for significant changes in variability, predictability, and slew rate of net electricity demand with implications for the stability of the local and distribution network and wider energy system.

The discrepancy between the peak modelled output of additional PV capacity derived from the rated output of the solar panels, and the output of the arrays as modelled is in the order of 22 - 24%. Our model assumes inverter losses of 14% so a further 8 – 10% relates to the cumulative distribution and orientation of PV panels and hourly variation in irradiance, as a result of changes in cloud cover. A more granular GIS model of the entire city-wide array based on actual roof orientation, tilt and shading, and more granular weather model would allow this to be evaluated in greater detail. From the simplified model used here it is not possible to determine whether this 'performance gap' is likely to increase or reduce when modelled at higher resolution. The annual energy yield (MWh/yr) for PV systems of different capacities is likely to be as important when considering emission reductions, and a more granular model should provide better estimates of these.

Utilizing all of the energy generated by the 1GW$_{peak}$ system would meet approximately half of the estimated annual electricity demand in Bristol in 2016, however this assumes no curtailment of supply when the output from the PV system exceeds electricity demand. As expected, and clearly shown in the model, the average daily energy output varies seasonally reflecting monthly changes in irradiance. Output also varies hourly as a consequence of changes in the azimuth of the sun and cloud cover. To avoid curtailment at times when output exceeds demand, would either require additional load (demand) or excess power to be diverted to other parts of the electrical distribution network, assuming there is capacity to accept this.

Demand side response (DSR) is already used to time-shift electricity usage, and to smooth peaks and troughs in demand by increasing or decreasing usage, and within the energy market there are mechanisms by which large commercial and industrial consumers, small to medium sized enterprises and aggregators can provide DSR services (NGESO-DSR, 2020). For domestic consumers fixed dual tariffs such as Economy 7 have existed since the introduction of storage heaters in the late 70's (Electricity Council., 1987). These use the differential between a day-time and cheaper night-time tariff to incentivize consumers to shift electricity usage to times when demand is low such as from midnight to 7am. More recently, domestic customers have had the option of Time of Use (TOU) energy pricing with the Octopus 'Agile' tariff (Octopus Energy, 2020), which is a domestic equivalent to a commercial half-hour electricity tariff. It too is intended to shift electricity usage from periods when demand and prices are high such as from 4pm to 7pm, to periods when both are low through alerts to customers and potentially through automated communication protocols with smart devices.

Given the availability of both commercial and now domestic time-of-use tariffs could predictive time-of-use tariffs be used to avoid curtailment of the output from high-capacity PV systems of the scale considered here? It seems highly likely that the temporal resolution, and accuracy of computer models used to predict electricity demand and local weather will continue to follow precedent and increase with computer processing power. However, at what point forecasts will be of sufficient resolution and reliability to predict variations in local cloud cover, such that outputs can be integrated into the half-hourly energy pricing, to address system variability, is unknown. A further issue with this approach is that half-hourly prices are set nationally, and triggering a local DSR response would require localized price signaling.

The temporal resolution in our simplified model, set by the PVGIS model is one hour, thus it is not possible to determine whether half-hourly price signals would be fast enough to trigger DSR responses to variations in output once the distributional effects of a large PV array are factored in. A more granular model with higher temporal resolution is needed to consider this in detail. However, as the relationship between the energy output of a PV panel and irradiance is a quantum mechanical one (Barnham, 2014), the variation in energy output in response to variations in cloud cover and

irradiance is instantaneous, meaning that PV systems have zero inertia. This suggests that predictive models would require a very high level of precision and temporal resolution to address changes in PV output from changes in cloud cover.

To smooth the peaks and troughs in net demand, reduce the slew rate and avoid curtailment, DSR must be synchronized with the net output of the PV array, for example increasing demand as the output from the PV array increases. Small errors in the synchronization and timing of DSR, leading for example to increasing demand when it should be reducing, could produce higher slew rates and greater instability in the local energy system.

An alternative to predictive modeling would be to use a characteristic variable of the energy system itself such as frequency (MacKay, D., 2011) to trigger DSR in real-time, thus eliminating the need for complex modeling and the risk of increasing variability and slew rate. The frequency of grid electricity falls when demand is greater than supply, and rises when the reverse is true. National Grid has an existing licence obligation to maintain the frequency of the electricity system at 50Hz plus-or-minus 1%, for which it uses dynamic frequency response, which is continuously on-line, and non-dynamic response, triggered by a defined frequency deviation, (NGESO-FRS, 2020) to stay within these limits. Within the energy market, suppliers of frequency response services can bid to National Grid to provide these under predefined categories. On the basis of this research, we suggest that the deployment of PV at scale is likely to require a parallel expansion of local DSR triggered and controlled by a real-time system output such as frequency. From a market and regulatory perspective this is quite different to the development of predictive responses based on half-hourly energy usage.

As discussed for the three levels of PV capacity considered here the slew rate in net demand increased by a factor between three and just under ten. Though our model specifically excludes the impact on net demand from additional DSR, the scale of the increase in the slew rate suggests that as well as a need to increase DSR capacity there may be a requirement for this to operate bi-directionally, that is be capable of operating as additional load and additional supply. The increased variability and amplitude of net demand observed, coupled with the zero inertia of PV systems also suggests a need for demand/supply capacity to be capable of switching rapidly from one state to another.

National Grid has used battery storage to provide grid balancing services since 2014 ('Electricity Explained: Battery storage | National Grid ESO', 2020). Given the national policy objective of transitioning to electric vehicles (BEIS a, 2020) and the availability of building integrated battery-storage solutions ('Battery storage | Centre for Sustainable Energy', n.d.), battery storage is an obvious candidate for providing additional bi-directional capacity. From a local authority policy perspective we may consider battery storage under three headings: i) building integrated battery storage, commonly though not exclusively using lithium ion batteries, with useable storage currently in the range of 3.5 to 13.2kWh (Jankowiak *et al.*, 2019) ii) standalone storage utilizing larger-scale lithium ion and flow batteries with capacities ranging from circa 200kWh to tens or hundreds of megawatt hours (International Renewable Energy Agency (IRENA), 2019) iii) batteries in electric vehicles currently in the range of 30 to 100kWh per vehicle. The capacity of both building-integrated and standalone storage options is easily scaled by virtue of a modular design. Large-scale storage is designed to be bi-directional but currently, with the exception of on-going trials (Western Power Distribution, 2019) ('Vehicle-to-Grid Trial: Building better grid for everyone | OVO Energy', n.d.), building-integrated storage and the battery storage in vehicles is not. The policy implications of additional demand for battery storage are discussed below.

Heat networks supplied by heat pumps could provide a further source of DSR where thermal storage capacity is sufficient to absorb intermittent heat inputs. Additionally, heat pumps providing space heating and hot water in high efficiency properties could also be operated dynamically to absorb excess electricity generation. Hydrogen generated by

electrolysis has also been mooted as a means of absorbing excess supply from renewable generation (IRENA, 2018) but is outside the scope of this paper and is not considered further here.

6.2 Policy, market and governance implications

6.2.1. Policy

We have shown that the deployment of large-scale PV in urban areas could make a significant contribution to annual electricity demand, provided curtailment measures can be implemented as PV capacity increases. However, the significant increase in the variability and predictability in hourly net electricity demand, which may become more complex as power demands from electrified transport and heat are integrated into the system, suggests the need for much closer collaboration between local and national policy makers and Distribution Network Operators (DNOs). We also suggest that the requirement for static battery storage and the battery storage capacity in electric vehicles (EVs) are both likely to increase as the installed capacity of PV grows. Therefore, local authorities should consider allocating sites for large-scale storage and bringing forward policies that will facilitate the development of vehicle-to-grid storage when developing EV charging infrastructure. This suggests the need for 'Fast' charging infrastructure to which vehicles are connected for extended periods of time rather than relying on 'Rapid' charge points to which vehicles are connected for short periods only. As local authorities are likely to be developing proposals for the deployment of EV charging infrastructure now, this is an area where further guidance would be of benefit. When framing policy objectives and setting local installation targets, allowance needs to be made for the discrepancy between the peak output of PV systems based on manufacturers' specifications and modelled outputs. In Great Britain, distribution network operators are currently in the process of transitioning from their traditional 'fit and forget' network operation role to a Distribution Systems Operator (DSO) role which emphasises active network management and using real-time data to make interventions on the network ('Energy Networks Association Open Networks Project DSO Implementation Plan Energy Networks Association Document Ref : 2021 WS3 DSO Implementation Plan Report Restriction: Public', 2021). However, network operators currently have limited visibility at a granular level (i.e. the low voltage network) and limited understanding of potential deployment patterns of distributed generation and flexibility assets. They are using DFES to scenario plan and increasingly working with local stakeholders but this is largely informal. As discussed above scenarios are high-level and divergent.

6.2.2 Market

The use of time-of-use (TOU) tariffs by commercial and non-domestic customers, and now domestic customers, could increase Demand Side Response (DSR) capacity in the short-term. However, our findings suggest that if DSR is deployed to address curtailment and system volatility resulting from high levels of PV, predictive modeling based on half-hour energy demand may be too imprecise for this purpose and risks worsening the effects it is intended to address. We suggest that real-time monitoring of system outputs using for example frequency, may be a more useful means of triggering mitigations such as DSR. We also suggest that static and vehicular battery storage will need to capable of operating bi-directionally and switching rapidly between supply and demand modes. Getting the capacity of battery storage to a scale where it is sufficient to balance the output from PV arrays of the sizes modelled here is likely to require mass participation by domestic and non-domestic consumers as well as service providers. This will require suppliers and retailers to create suitable tariffs and appealing charging packages to attract customers. It will also require the development of applications that will allow customers to participate in this market simply with minimum input.

6.2.3 Governance

Whilst there is an obvious match between power output from solar PV, and daily energy demand in UK cities, the backcasting approach employed here suggests that high levels of PV concentrated in an urban area, will produce a far more complex and dynamic local energy system than at present. Without mitigation the potential for carbon savings and the cost benefits of embedded PV at scale will be lost, and it is more likely to be a liability and a net cost to the energy system and consumers. This implies the need for a market framework that both stimulates and maintains the provision of local system balancing services and a regulatory framework to allow a far more complex energy system to operate coherently and efficiently. We suggest that as the energy system becomes more complex, due to increased renewable energy generation and the electrification of heat and transport, the use of half-hourly energy pricing based on predictive modelling, to smooth peaks and troughs in demand, may be too slow and imprecise to respond to the variability in system output. This may need to be replaced with real-time monitoring and an amended system for setting and adjusting the price of electricity. We suggest that the need for bi-directional storage is likely to increase as PV generation capacity expands, and regulation (Ofgem, 2019) will need to be amended to enable all forms of battery storage, including that in vehicles to export to the distribution network and grid. One further issue related the reduction in system inertia and the proposed use of frequency to trigger demand and supply responses to instability, which has both technical and regulatory implications, is the potential for interactions between different segments of the distribution network to create positive feedback which induces wider instability across the distribution network. This would benefit from further research.

6.3 Conclusions

In this paper we have combined energy backcasting with a simplified ball-park model to explore the policy, market and governance implications of a specific policy measure, namely the installation of photo-voltaic panels at scale within an urban area, using the city of Bristol in South West England as a case study. This is in the context of political commitments made by local councils across the UK in response to the climate emergency which if realized, will require very deep, rapid and permanent reductions in local emissions. By backcasting from specific end-points we have been able to consider the possible implications of policies designed to increase the uptake of PV, should these be successful and implemented fully.

Within a suite of possible interventions there are strong technical and policy reasons for local government to consider measures that would increase the uptake of PV. We have shown that at very high levels ($1GW_{peak}$) PV could meet almost half the annual requirement for electricity in Bristol (based on estimated consumption in 2016) provided output is not curtailed when supply is greater than demand. However, at this scale PV also becomes the dominant source of variability in net demand, and having zero inertia has the potential to disrupt the stability of a local energy system, as output varies in response to changes in irradiance due to the formation and movement of clouds. This suggests that for very high levels of PV generation to be of benefit there will need to be close collaboration between policy makers and Distribution Network Operators (DNOs). Furthermore, it has implications for other possible policy measures such as EV charging, the development of products and services within the energy market, the use of half-hourly predictive energy pricing and for the governance and regulation of the market itself.

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Mark Letcher is a former employee of Bristol City Council. In 2017 he was a member of the team with responsibility for commissioning the following report: Walker, I., and Jennison, N. (2018) *Element Energy, An evidence based strategy for delivering zero carbon heat in Bristol An evidence based strategy for delivering zero carbon heat in Bristol A report for Bristol City Council*.

Mark Letcher is a former employee of The Centre for Sustainable Energy (CSE). A technical report produced by The Centre for Sustainable Energy has been cited in this paper.

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