PERFORMANCE OF DISTRIBUTED PV IN THE UK: A STATISTICAL ANALYSIS OF OVER 7000 SYSTEMS

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ABSTRACT: In June 2015, the UK fleet of solar photovoltaic (PV) systems reached 7.8 GWp of capacity, but there are wide gaps in our understanding of the performance of these systems, which has lead to the conservative limit of 10 GWp being imposed on UK PV capacity by the Department of Energy and Climate Change. Here we present the results of a statistical analysis of real world UK PV systems which donate data to the Microgen Database, of which there are over 7000. The mean yearly-integrated Performance Ratio (*PR*) of domestic scale UK PV is 83% with a standard deviation of 7%. By considering yearly-integrated *PR*, we have shown that 4.1 % of systems suffered long-term underperformance relative to their nominal efficiencies during 2013. The mean degradation rate for crystalline Silicon-based PV systems in the UK is -0.8 ± 0.1% per year. The state-of-the-art of UK PV, in terms of technology, manufacturing, and installation-standards, is found to have increased by 1% per year between 2002 and 2013.
Keywords: System Performance, Degradation, Small Grid-connected PV Systems

1 INTRODUCTION

In June 2015, the UK fleet of solar photovoltaic (PV) systems reached 7.8 GWp of capacity [1]. Previous works have studied the performance of some PV systems in the UK [2], but there are few publications [3] which study an ensemble of systems representative of the UK fleet, leading to gaps in our knowledge of real-world performance of distributed PV in the UK. This work explores the real-world generation of over 7000 distributed PV systems from the Microgen Database (MgDB) [4], in order to characterise and quantify performance. The resulting statistics will help to inform both academia and industry, whilst also informing Government policy with respect to PV. We explore areas of key interest to stakeholders such as performance ratio (*PR*), state-of-the-art and degradation.

These results are highly relevant to the decision making process undertaken by policy makers in the UK due to the implications for cost analysis of incentives and ensuring effective integration into the electricity network. This is especially true at the time of writing, since the Department of Energy and Climate Change (DECC) for the UK Government recently opened a consultation on a review of Feed-in Tariffs (FITS) for micro-generation PV to take place in January 2016 [5].

Several thousand PV systems have been monitored since 2010, with some systems' historic data spanning over 7 years. The performance of UK PV has been characterised by deriving statistics regarding key performance metrics; *PR* at a monthly and yearly integration and *PR* at standard test conditions (*PR@STC*). These metrics then provide the basis for assessing improvements in the state-of-the-art of PV as well as deriving an indicative measured degradation rate for PV performance in the UK.

2 DATA AND METHOD

2.1 Data

Distributed PV generation data is collected via the MgDB website [4], with PV owners using the site as a portal to upload readings and in return receiving free monthly Performance Ratio (*PR*) analysis and peer-to-peer performance checking in the form of interactive maps and nearest neighbour comparisons. The majority of data is measured by the energy meters of the inverters and is collected from commercial data donors who own/monitor hundreds of systems using automated data transfers. *PR* calculations interact directly with the MgDB so as to provide regular updates to the live website.

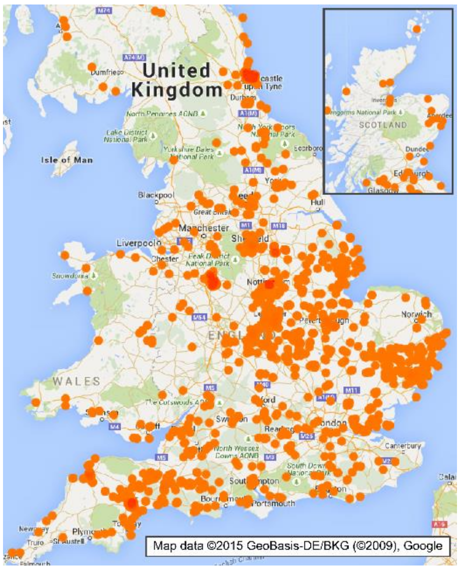

***Figure 1**; Map of the MgDB systems used in this analysis.*

The complete dataset of MgDB comprises PV generation data from more than 7000 PV systems across UK (see), at various temporal resolutions (typically 10-min, 30-min, daily or monthly), with historic data spanning up to seven years [MgDB], although most of the PV systems were installed after 2011. The dataset is supplied by a combination of homeowners and commercial sources and includes both domestic and commercial scale installations between 0.7 and 69 kWp with a wide range of orientation and tilt angles. The data from the MgDB has been subjected to rigorous checks and validations in order to isolate and remove as much erroneous data as possible. The standard set of filters employed prior to analyses is:

- Use only single array systems since generation data cannot be decomposed into constituent arrays.
- Use only systems within the UK. This is necessary since the MgDB website accepts systems from anywhere in the world, although in reality only a very small proportion lies outside of UK.
- Use only systems with $0° \leq orientation\ from\ south \leq 90°$ and $0° < tilt\ from\ horizontal \leq 60°$.

In some cases system data is investigated manually to verify to a good degree of confidence that the data should be removed, for example when considering systems whose orientation or tilt appears incorrect. After the reading requirements and system validation has been carried out 4369 systems remain, which are analysed in this study.
Data from the MgDB is prone to human errors on the part of the donor, for example, entering incorrect system parameters such as orientation, tilt or installed capacity. Some of these errors lead to outliers in the distribution of *PR* and/or *PR@STC* which can skew non-robust statistics such as the mean, μ, and standard deviation, σ. It is therefore crucial that we are able to identify and isolate them from the analysis. A simple and reliable method for removing outliers from a symmetrical distribution is Tukey's method [6], which uses the outlier limits in Equation (1).

$$\begin{gathered} Upper\ limit = Q_3 + 1.5 \times IQR \\ Lower\ limit = Q_1 - 1.5 \times IQR \\ Inter\ Quartile\ Range, IQR = Q_3 - Q_1 \\ Q_1 = 25^{th}\ percentile, Q_3 = 75^{th}\ percentile \end{gathered} \qquad (1)$$

Tukey's method proves useful when the aim is to remove all outliers which do not form part of the symmetrical distribution, which in this context corresponds to systems that are performing correctly i.e. no underperformance. This is desirable when we investigate the degradation since we want our result to be representative of a fully functioning PV system i.e. we are only interested in degradation and in the case of underperforming systems we cannot distinguish between the degradation and underperformance due to other factors.

When analysing the distribution of yearly-integrated *PR*, it is desirable to include the results for under-performing systems whilst excluding any outliers due to erroneous data and complete failures. This is complicated by the fact that the distribution takes the shape of a Weibull distribution [7] [8] which is non-symmetric and features a long tail at lower values. To achieve this, we employ a method developed specifically in the context of PV fault detection [9] whereby the upper limit is the median, $\mu_{1/2}$, plus $3\sigma_{1/2}$ and the lower limit is $\mu_{1/2}$ minus $6\sigma_{1/2}$ (Equation (2)). The statistic $\sigma_{1/2}$ is the standard deviation of all values above the median, that is, the standard deviation of the observed normal part of the distribution.

$$\boldsymbol{\sigma_{1/2}} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{N_{1/2}}}\sum\left[\boldsymbol{PR} - \boldsymbol{\mu_{1/2}}\right]^{\mathbf{2}}} \qquad (2)$$

2.2 Irradiation

Monthly Global Horizontal Irradiation (*GHI*) has been interpolated at each of the sites from the UK Met Office (UKMO) ground based pyranometers [10] using an inverse distance weighted interpolation as per the methodology documented by Colantuono et al. [3]. As with Colantuono et al., the exponent of the inverse distance is chosen to minimise the mean error across all UKMO stations using leave-one-out cross-validation (LOOCV). By applying LOOCV to 96 months (2011-2014) of interpolated monthly irradiation data, the mean absolute percentage error (MAPE) of this interpolation method in UK has been calculated as 5.0%, whilst the mean percentage error (MPE) of all months, 0.1%, reveals negligible bias overall. The resulting overall root mean square error (RMSE) is 4.5%. For this LOOCV we use the 5%-trimmed-mean in place of the mean to account for and remove the effect of highly localised weather conditions, which are circled in red in Figure 2. These uncertainty estimates are in line with those reported by Colantuono et al. We have calculated the 5% trimmed MPE for each season during the four year period and find the range to be between 0.1 and 0.2%, indicating that this interpolation method is in general resilient to bias in all seasons. The MAPE increases in winter relative to summer, with values of 4, 4, 5 and 7% for spring, summer, autumn and winter respectively.

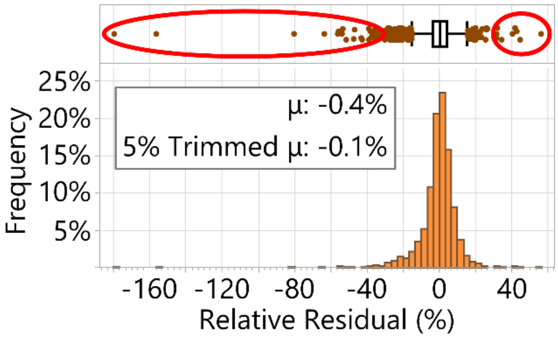

Figure 2; *Distribution of errors for interpolated irradiation using LOOCV across 96 months.*

The interpolated monthly *GHI* is decomposed into direct and diffuse components according to Page [11]. The direct and diffuse components are then transposed to the inclined plane and summed to give the Global Tilted Irradiation (*GTI*) using Klein & Theilacker [12].

2.3 Monthly and yearly-integrated *PR*

Performance Ratio (*PR*) is widely used metric for comparing relative performance of PV systems whose design, technology and location differ [13]. *PR* is defined in Equation (3):

$$\boldsymbol{PR} = \frac{\boldsymbol{\eta_{achieved}}}{\boldsymbol{\eta_{spec}}} = \frac{\boldsymbol{E}/\boldsymbol{I_{POA}}}{\boldsymbol{\eta_{spec}}} \qquad (3)$$

Where $\boldsymbol{\eta_{achieved}}$ and $\boldsymbol{\eta_{spec}}$ are the achieved efficiency and nominal efficiency (according to the manufacturer) of the system respectively (dimensionless); $\boldsymbol{E}$ is the energy generated by the system (kWh) and $\boldsymbol{I_{POA}}$ is the irradiation incident in the plane of the array (kWh). The achieved efficiency must be calculated over some arbitrary period. In the case of a yearly period, we refer to the *PR* as the yearly-integrated *PR* in order to distinguish it from the mean of the monthly *PR* across all months in the year, which is not studied here.

We have analysed the distribution of the yearly-integrated *PR* on a histogram after applying the outlier removal technique described by Equation (1) and have fitted several continuous distributions in order to quantify the shape of the distribution and offer reproducibility. We have graphed mean monthly *PR* across all systems in order to demonstrate seasonal variability.

2.4 Monthly *PR@STC*

PR fails to take into account the module efficiency response to variations in module temperature and irradiance intensity. In the UK these factors are highly seasonal and as a result there is a significant seasonal and inter-annual variation in the measured *PR*. The so-called Performance Ratio at Standard Test Conditions (*PR@STC*) attempts to correct for these effects by introducing correction terms to the *PR* calculation. According to the US National Renewable Energy Laboratory (NREL) [14], *PR@STC* is given by Equation (4):

$$\boldsymbol{PR@STC} = \frac{\boldsymbol{PR}}{\boldsymbol{f_T \times f_G}}$$
$$\boldsymbol{f_T} = \left[\mathbf{1} - \frac{\boldsymbol{\delta}}{\mathbf{100}}(\boldsymbol{T^*_{cell}} - \boldsymbol{\overline{T}_{cell}})\right] \qquad (4)$$
$$\boldsymbol{f_G} = \left[\mathbf{1} + \boldsymbol{c}\ \mathbf{ln}\left(\frac{\boldsymbol{G_{POA}}}{\boldsymbol{G^*}}\right)\right]$$

Where $\boldsymbol{PR}$ is the uncorrected monthly *PR*; $\boldsymbol{\delta}$ is the temperature coefficient of power for the installed modules (%/°C, negative in sign); $\boldsymbol{T^*_{cell}}$ is the cell temperature at STC (25 °C); $\boldsymbol{\overline{T}_{cell}}$ is the irradiance-weighted mean cell temperature for the month (°C, see Equation (5)); $\boldsymbol{c}$ is a parameter describing the reduction in efficiency due to decreased irradiance (0.031 for crystalline Silicon cells based on $\frac{\eta_{200}}{\eta_{1000}} = 0.95$); $\boldsymbol{G_{POA}}$ is the mean irradiance-weighted irradiance in the plane of the array for the month (W/m^2) and $\boldsymbol{G^*}$ is the irradiance under STC (1000 W/m^2). The irradiance-weighted mean cell temperature, $\boldsymbol{\overline{T}_{cell}}$, is given by Equation (5):

$$\boldsymbol{\overline{T}_{cell}} = \frac{\sum_j[\boldsymbol{T_{cell}(j)} \times \boldsymbol{G_{POA}(j)}]}{\sum_j \boldsymbol{G_{POA}(j)}} \qquad (5)$$

Where $\boldsymbol{T_{cell}(j)}$ and $\boldsymbol{G_{POA}(j)}$ are the cell temperature and irradiance respectively at hour $\boldsymbol{j}$; and $\boldsymbol{\Sigma_j}$ is the summation over all hours in the month.

The cell temperature at each hour is estimated using the Sandia PV Array Performance model [15], which takes irradiance, ambient temperature, wind speed and module parameters as inputs. Conveniently, the Sandia model is available in the "PV_LIB Matlab" library, made available as an open-source project by the Sandia National Laboratories PV Performance Modelling Collaborative [16]. The module parameters determine the heat transfer coefficients, $\boldsymbol{a}$, $\boldsymbol{b}$ and $\boldsymbol{\Delta T}$, according to the type of array; for these analyses we use the "Glass/cell/glass" and "Close-roof mount" values of -2.98, -0.0471 and 1°C respectively, as recommended by King and Boyson [15].

Since $\boldsymbol{\overline{T}_{cell}}$ requires hourly irradiance, ambient temperature and wind speed data, we have only considered systems close to (within 20 km of) UKMO weather stations, where this data is readily available.

2.5 System level performance degradation

Monthly *PR@STC* during the months April to September has been shown to be stable (Figure 6 and 7) and so it provides a useful benchmark for year-on-year comparisons of performance. By analysing the monthly *PR@STC* during these months on a per system basis over several years, we have derived an indicative value for the relative system level performance degradation of UK distributed PV during the first years of operation. This is achieved by first normalising the April-September *PR@STC* of each system to the earliest value and then fitting a straight line to the data with a fixed intercept of 1. Here we present a histogram of the resulting degradation rates and derive an average rate using robust statistics. In order to be included, a system must have at least 5 monthly *PR@STC* data points spanning at least 3 years.

2.6 State of the art

We have assessed the improvement in the state of the art of the PV systems installed in the UK by analysing yearly integrated *PR* as a function of installation date. A linear fit on the resulting graph is used to extract the rate of improvement in the state of the art of UK distributed PV. Because the date of installation was not available for all of the PV systems of the MgDB, we have used the production start date of the installed modules as a proxy for installation date. In doing so, we have accurately represented improvements in state of the art due to the supply-chain and manufacturing process, but will have introduced some uncertainty with regards to installation standards since there may be some lag in the correlation between production start date and install date.

3 RESULTS AND DISCUSSION

3.1 Monthly and yearly-integrated *PR*

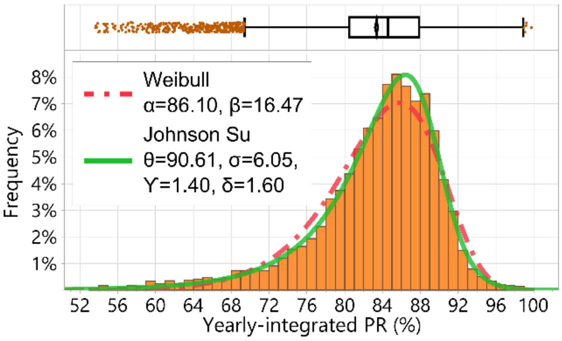

Figure 3*; Histogram of yearly-integrated PR across all years of data.*

The distribution of yearly-integrated *PR* is presented in Figure 3. The shape is characterised by a Weibull type distribution whereby the normal uncertainty in the *PR* calculation is superimposed with a long tail to lower values, corresponding to underperforming systems. We also fit a Johnson Su distribution in order to provide reproducibility. The mean yearly-integrated *PR* is 83.33% with a standard deviation of 6.68% and a standard error of 0.08%. The median yearly-integrated *PR* is 84.60%. The boxplot in Figure 3 displays the Tukey outlier limits discussed earlier and demonstrates why such limits are effective in removing underperforming systems, i.e. systems in the tail of the distribution. The mean is higher than the values reported recently across Europe [8] [17]

[18]. Some of this discrepancy may be due to uncertainties in the interpolation of *GHI* at the location of the system since each source of irradiation data will be subject to different errors. For example, irradiation data from the Climate Monitoring Satellite Application Facility (CM-SAF) has been shown to be subject to bias errors of more than +15% [19], with a relative mean bias error of +6.2% in the UK. Another potential source of discrepancy is the transposition of *GHI* to *GTI*.

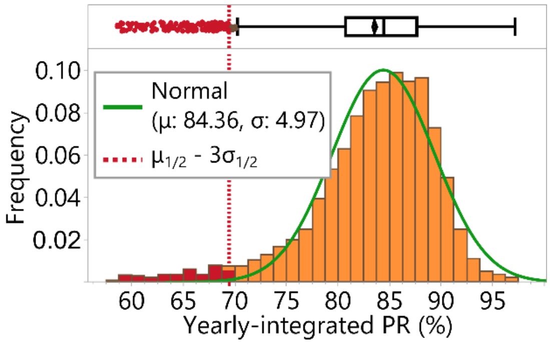

***Figure 4**; Histogram of yearly-integrated PR in 2013. Data highlighted in red correspond to systems experience long term underperformance according to our $\mu_{1/2} - 3\sigma_{1/2}$ rule.*

By considering systems with yearly-integrated *PR* less than $\mu_{1/2} - 3\sigma_{1/2}$, we can determine the proportion of systems that are deemed to be underperforming with respect to their peers. Figure 4 presents the distribution of yearly-integrated *PR* for all systems in 2013 once erroneous data has been removed according to the $6\sigma_{1/2}/3\sigma_{1/2}$ rule discussed earlier. The normal part of the distribution has been fitted using $\mu = \mu_{1/2}$ and $\sigma = \sigma_{1/2}$, with underperforming systems highlighted in red. Of the 4181 systems, 171 are deemed to have underperformed in 2013, equivalent to 4.1%.

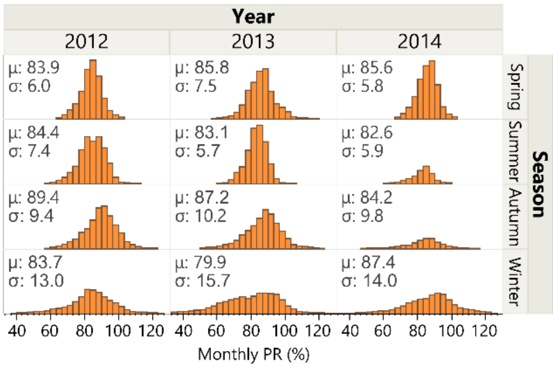

***Figure 5**; Histograms of monthly PR by year and season for 2012-2014.*

In figure 5 we see the distribution of monthly *PR* broken down into seasons across 3 years of data. It is clear from the spread in the histograms and the standard deviations that the *PR* is less variable in the summer months than in winter, with spring and autumn falling somewhere in between. Figure 5 also reveals the year-on-year variation to be significantly less during summer than in winter, with ranges of 1.8% and 7.5% respectively. This trend is consistent with that reported in other European countries with similar climate [8] [17] [20]. For these reasons, monthly *PR* is of limited use as a means to monitor PV systems for underperformance and faults.

3.2 Monthly *PR@STC*

As with *PR*, the *PR@STC* is more variable in winter than in summer, making it of limited use as a monitoring tool (Figure 6). With *PR@STC* the dip in summer due to increased temperatures is less pronounced [7] whilst a pronounced dip in winter indicates underperformance during these months. The main driving factor for this underperformance is thought to be increased shading as a result of lower solar elevation angles, but the drop in efficiency of inverters at lower generation levels may also contribute.

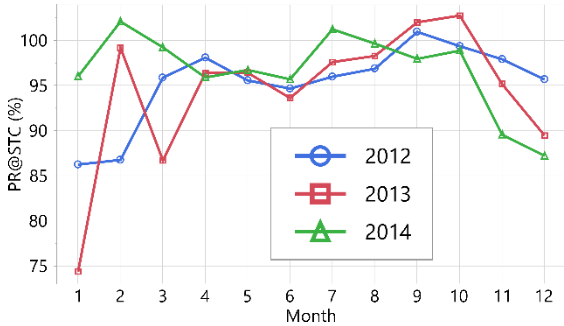

***Figure 6**; Mean monthly PR@STC for 2012-2014.*

Figure 7 compares the standard deviation in the measured *PR@STC* for each month over all available systems and all available years. In order to eliminate the effect of underperforming systems, *PR* and *PR@STC* values were removed according to the Tukey outlier limits. In general the *PR@STC* shows less variance and is therefore an improvement over *PR*, but the increased standard deviation during winter months relative to summer means it is still problematic. Figure 7 demonstrates that *PR@STC* is consistently accurate from April to September inclusive and so we choose this period to assess year-on-year degradation.

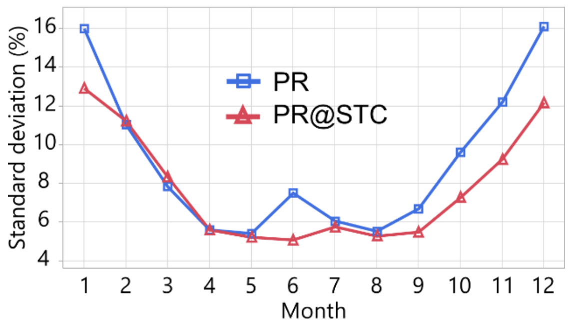

***Figure 7**; Standard deviation of the PR and PR@STC for each month across all years and all systems.*

3.3 System level performance degradation

Before analysing the distribution of degradation rates, we remove those that fall outside Tukey outlier limits. These systems are badly fit by straight line, most probably because of temporary faults or down time. We weight the distribution according to the number of years of data available for each system, since this will effectively weight towards more reliable fits. The resulting degradation rate will only be representative of the MgDB sample, which is overwhelmingly comprised of crystalline Silicon technology.

The skew (Pearson's moment coefficient of skewness) of -2.5 indicates definite shift in distribution towards negative values. The mean degradation is -0.8% per year with a standard error of 0.1%, whilst the median is -0.5% per year. These values are in good agreement with literature [21] [22]. The 95% confidence interval for the mean lies between -0.6 and -1.0 % per year.

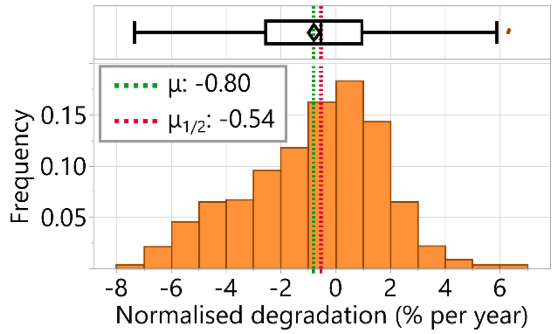

Figure 8*; Histogram of degradation rates calculated for all systems from PR@STC. It is important to note that the spread in the distribution should be attributed to the uncertainty in the PR leading to uncertainty in the degradation.*

It is worth noting that the resulting mean differs slightly depending on whether *PR@STC* outliers (underperforming systems) are included or excluded. The mean without outliers is -0.8%, whilst the mean with outliers is -0.9% per year. It is not possible to discern whether the underperforming systems are such because of increased degradation, or whether the nature of the fault that caused the underperformance has then led to increased degradation. It is therefore appropriate to exclude the outliers, and the resulting mean can be seen as representative of the degradation experienced by systems that have not developed any specific faults.

3.4 State of the art

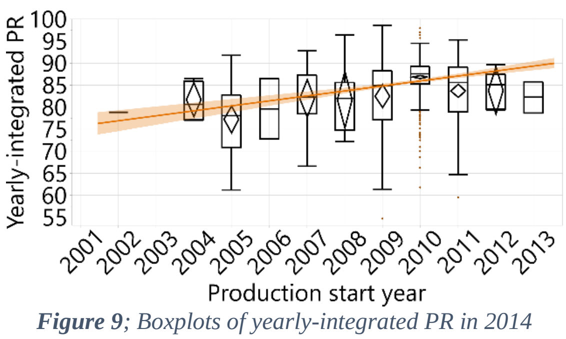

Figure 9*; Boxplots of yearly-integrated PR in 2014 against production start year of the installed modules. Orange line shows a linear best fit with gradient of 1% per year. The orange shaded area shows the 95% confidence interval for the linear fit.*

Figure 9 shows the 2014 yearly-integrated *PR* of 866 systems against the production start year of the installed modules. The gradient of the linear fit implies that the system performance has increased by 1.1% per year. A similar fit to 2012 and 2013 yearly-integrated *PR* data yields gradients of 0.97 and 0.95% from 348 and 890 systems respectively. We use the mean of these values weighted according to the number of systems each year in order to calculate the improvement in the state-of-the-art of UK PV to be 1.0% per year. This is lower than previously reported [7], but is more robust thanks to a thorough outlier removal process and the inclusion of more than one year's yearly-integrated *PR* data. The 95% confidence interval for the gradient is 0.68 to 1.4% per year. The increase in performance is thought to be driven by improvements in the manufacturing and distribution process as well as improvements in installation standards. The implication for the UK PV industry is that the state-of-the-art of small-scale PV has improved by 10% over the last decade.

4 CONCLUSION

We have presented a detailed statistical analysis of a large ensemble of UK domestic scale PV, focusing on statistics of crucial importance to policy makers, industry and academia. The yearly-integrated *PR* in the UK is found to be higher than the equivalent statistic reported in other European countries [8] [17] [18]. The discrepancy with European studies requires further investigation as it is not clear whether this arises from genuine physical phenomenon or some undiagnosed source of bias in this or the other studies considered.

We have identified that 4.1% of PV systems suffered long term underperformance during 2013, which is also indicative of the underperformance rate in other years.

We have presented a mean degradation rate for crystalline Silicon of -0.8 ± 0.1% per year in the UK, which is in good agreement with values reported elsewhere [21] [22].

We have established an improvement in the state of the art of the UK PV industry of 1% per year between 2002 and 2013, amounting to a 10% improvement in the last decade.

5 REFERENCES

[1] UK Office of Gas and Electricity Markets (OFGEM), "Feed-in Tariff Installation Report 30 June 2015," 06 07 2015. [Online]. Available: https://www.ofgem.gov.uk/environmental-programmes/feed-tariff-fit-scheme/feed-tariff-reports/installation-reports. [Accessed 11 09 2015].

[2] E. A. Essah, A. R. Arguelles and N. Glover, "Assessing the performance of a building integrated BP c-Si PV system," Renewable Energy, vol. 73, pp. 36-45, 2014.

[3] G. Colantuono, A. Everard, L. M. Hall and A. R. Buckley, "Monitoring nationwide ensembles of PV generators: Limitations and uncertainties. The case of the UK," Solar Energy, vol. 108, pp. 252-263, 2014.

[4] Sheffield Solar, "Microgen Database," Sheffield Solar - University of Sheffield, [Online]. Available: http://www.microgen-database.org.uk/.

[5] UK Department of Energy and Climate Change (DECC), "Consultation on a review of the Feed-in Tariffs scheme," 27 08 2015. [Online]. Available: https://econsultation.decc.gov.uk/office-for-

renewable-energy-deployment-ored/fit-review-2015. [Accessed 15 09 2015].

[6] J. W. Tukey, Exploratory Data Analysis, Addison-Wesley, 1977.

[7] J. Taylor, J. Leloux, A. Everard, J. R. C. Briggs and A. Buckley, "Monitoring thousands of distributed PV systems in the UK: Energy production and performance," in PVSAT-11, Leeds, 2015.

[8] J. Leloux, L. Navarte and D. Trebosc, "Review of the performance of residential PV systems in France," Renewable and Sustainable Energy Reviews, vol. 16, no. 2, pp. 1369-1376, 2012.

[9] J. Leloux, L. Navarte, A. Luna and A. Desportes, "Automatic fault detection on BIPV systems without solar irradiation data," in 29th European Photovoltaic Solar Energy Conference and Exhibition, Amsterdam, 2014.

[10] Met Office, NCAS British Atmospheric Data Centre, "Met Office Integrated Data Archive System (MIDAS) Land and Marine Surface Stations Data (1853-current)," 2012. [Online]. Available: http://catalogue.ceda.ac.uk/uuid/220a65615218d5c9cc9e4785a3234bd0. [Accessed 11 09 2015].

[11] J. Page, "The estimation of monthly mean values of daily total short-wave radiation on vertical and inclined surfaces from sunshine records for latitudes 40ºN–40ºS," in Proc. UN Conf. on New Sources of Energy, 1961.

[12] J. A. Klein and J. C. Theilacker, "An Algorithm for Calculating Monthly-Average Radiation on Inclined Surfaces," Journal of Solar Energy Engineering, vol. 103, pp. 29-33, 1981.

[13] US National Renewable Energy Lab (NREL), "Performance parameters for grid-connected PV systems," in Photovoltaic Specialists Conference, 2005. Conference Record of the Thirty-first IEEE, Florida, 2005.

[14] S. Kurtz, J. L. B. Cruz, E. Riley and C. Hansen, "Weather-Corrected Performance Ratio," April 2013. [Online]. Available: http://www.nrel.gov/docs/fy13osti/57991.pdf. [Accessed 13 January 2015].

[15] D. L. King, W. E. Boyson and J. A. Kratochvill, "Photovoltaic Array Performance Model," Sandia National Laboratories, 2004.

[16] Sandia National Laboratories, "PV Performance Modelling Collaborative (PVPMC)," 2014. [Online]. Available: https://pvpmc.sandia.gov/. [Accessed 17 09 2015].

[17] J. Leloux, L. Navarte and D. Trebosc, "Review of the performance of residential PV systems in Belgium," Renewable and Sustainable Energy Reviews, vol. 16, no. 1, pp. 178-184, 2012.

[18] A. Woyte, "Monitoring of photovoltaic systems: good practices and systematic analyses," in 29th European Photovoltaic Solar Energy Conference and Exhibition, Amsterdam, 2014.

[19] T. Huld, R. Muller and A. Gambardella, "A new solar radiation database for estimating PV performance in Europe and Africa," Solar Energy, vol. 86, p. 1803–1815, 2012.

[20] J. Leloux, R. Moreton, L. Navarte, J. Taylor, D. Trebosc and A. Desportes, "Monitoring 30,000 PV Systems in Europe: Performance, Faults and Stateof the Art," in 31st European Solar Energy Conference and Exhibition (EU PVSEC 2015), Hamburg, 2015.

[21] D. C. Jordan and S. R. Kurtz, "Photovoltaic Degradation Rates — An Analytical Review," Progress in Photovoltaics: Research and Applications, vol. 21, no. 1, pp. 12-29, 2013.

[22] B. Muller, L. Hardt, A. Armbruster, K. Kiefer and C. Reise, "Yield Predictions for Photovoltaic Power Plants: Empirical Validation, Recent Advances and Remaining Uncertainties," in 29th European PV Solar Energy Conference and Exhibition (EU PVSEC 2014), Amsterdam, 2014.