SPATIO-TEMPORAL ANALYSIS OF PV DIFFUSION PATTERNS: AN INTEGRATED NEURAL NETWORKS AND AGENT-BASED MODEL

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Abstract

Photovoltaic (PV) panels offer significant potentials for contributing to the UK's energy policy goals relating to decarbonisation of the energy system, security of supply and affordability. The substantive drop in the cost of panels since 2007, coupled with the introduction of the Feed-in Tariff (FiT) Scheme in 2010, has resulted in a rapid increase in installation of PV panels in the UK from 16.1MW installed capacity in 2010 January to 12.4GW by 2017 December. Yet, spatial and temporal diffusion of PVs show significant differences across the UK.

By creating reverse flows on the networks, especially at low voltage distribution networks, domestic PVs present a key challenge for network operators to manage the grid such that there is enough capacity and voltage headroom available to accommodate these flows. That's why understanding spatio-temporal diffusion of PVs can provide valuable insights to both network operators and policy makers with a view to predict and shape their future deployment.

To date, different approaches have been used for analysing PV diffusion process, including (i) spatial regression, (ii) agent-based modelling (ABM) and (iii) epidemic models. These approaches present different strengths and weaknesses.

The spatial regression and epidemic models characterise the adoption process at a geographical scale (i.e. an aggregated level) to analyse the impact of independent

variables on the PV diffusion at different scales from neighbourhood, city level up to national level. ABMs on the other hand focus on the individual decision-making process, taking into account other individuals' choices in the agent's network and their interactions so as to capture emerging social dynamics.

While spatial regression and epidemic models overlook the temporal dimension of the diffusion process, ABMs have limited capacity in representing large populations and characterising temporal aspects explicitly. Moreover, many ABMs are driven by rational choice theory arguing that agents have access to perfect information to undertake complex calculations to evaluate gain in their utility. The aim of this work to address these limitations by developing a novel agent-based model where agents are defined as geographical areas (rather than as individuals as commonly done). The agents' decision-making process is defined by artificial neural networks (ANN) so that we can analyse the spatial-temporal diffusion of PVs by taking into account both peer effects and underlying spatial regularity of diffusion patterns as informed by spatial econometrics literatures. Drawing from computer and complexity sciences, geographical information systems and energy economics, and using socioeconomic data at Post Code level, the model has the following novel aspects:

- The ANN's ability to improve agent's decision-making process by taking into account socioeconomic time series data
- The ABM's ability of characterise the social dynamics at large scale using spatially explicit data sets
- The ANN's capability to capture the evolution of the system using explicit time-horizon

The initial prototype model is developed for the City of Birmingham focusing on the PV adoption process. Our initial auto-regressive model predicts future diffusion patterns at post-code level on a monthly basis. Both limited availability of time series data and spatial influence of other agents' estimations on a given agent's estimation lead to accumulation of errors spatio-temporally. Emerging results using socio-economic variables highlight the importance of income, electricity consumption and the household size. We also detect strong spatial dependency in the diffusion patterns.

Overall this work will produce novel insights on the potential spatial PV clustering, then, that may help distribution network operators to develop better strategies to accommodate higher loads which will, in turn, help keeping the energy affordable for consumers. The model can be used further to analyse the impacts of alternative policies to influence PV adoption, such as the development of local economic incentives.

Keywords: Spatial diffusion of innovations; Agent-based modelling; Solar photovoltaic adoption; Artificial neural networks; Spatio-temporal modelling.

1 Introduction

This paper builds on the three recurrent modelling approaches found in the literature: ABM, spatial regression and the epidemic models. Their common features, key assumptions as well as the aspects that we modify in our approach are presented next.

The ABMs that have analysed the PV adoption process have commonly characterise agents as housholds, either considering the homeonwer's socioeconomic characteristics or the dwelling's economic and physical characteristics. Frequently, the decision-making process is based on the Theory of Planned Behaviour. Then, model assumes that each agent has a dynamic "*attitude*" towards adopting PV, and the agents adopt if this attitude is greater than a threshold that is common for all the agents. Then, agents' initial attitude is calculated based on survey data, and this is modified at each step of the simulation by the interaction with other agents in its own social network. Significant costs and time associated with surveys have led some researchers to find alternative variables to calculate the agent's attitude (Haifeng et al., 2014; Müller and Rode, 2013; Rai and Robinson, 2015; Robinson et al., 2013; Robinson and Rai, 2015).

The econometric ond spatial-econometric approaches characterise the PV adoption process at local level (census tracks, regional geographical areas, block-group, postcode) using an econometric model that considers the spatial dimension of the adoption process. The model assumes (i) that individuals decision-making is affected by the observation of the PVs, thus, the social effect is based on the number of installed PVs spatially close to the locations; (ii) the outcome is the accumulation of individual choices, and is defined by the number of PV installations in a specific location, at any specific month; (iii) the model considers independent and identically distributed estimation errors; this term is used to capture any *non-predicted* behaviour in the data. For future research, the authors suggest (i) to take into account the social effect that occurs between areas (spill over effect). (ii) Extend the model from auto-regressive to a multivariable approach, and explore the variation of results when changing the study scale. (iii) Finally, to improve the model replacing the regression with a non-linear model to capture the non-linear PV data's behaviour and its temporal dynamics (Balta-Ozkan, Yildirim and Connor, 2015; Davidson et al., 2014; Graziano and Gillingham, 2015; Kwan, 2012; Langheim, 2014; Schaffer and Brun, 2015).

Finally, the epidemic models have modelled the PVs' adoption process at local level (census tracks). These models are based on the Poisson distribution, and assumes that at individual level there is no explanatory elements for any decision taken during the adoption process. Hence, the decision-making criteria is not deterministic. Also, the agents' interaction is not fixed to any particular network. Then, the model is constructed considering that (i) there are a limited number of contacts (interactions) made at each period of time and is defined by the population density; (ii) it is not essential to know the specific individual's network in order to understand the general diffusion process; And (iii) the model's degree of uncertainty deepens on the study scale. The micro scale (individual level) can potentially assess the probability of adoption, with a high degree of uncertainty. On the other hand, macro scale (aggregated level) studies may provide the general adoption pattern, with a lower degree of uncertainty (De Groote, Pepermans and Verboven, 2016; Rode and Weber, 2016). The authors note that future work could explore the impact of peer-effect into the decision process as well as examine the impact of temporal changes in the explanatory variables on the adoption rate.

The aim of this work is to advance the agent-based modelling by developing a novel agent-based model where agents are defined as geographical areas (rather than as individuals as commonly done). The agents' decision-making process is defined by artificial neural networks (ANN) so that we can analyse the spatial-temporal diffusion of PVs by taking into account both peer effects and underlying spatial regularity of diffusion patterns as informed by spatial econometrics literatures. Drawing from computer and complexity sciences, geographical information systems and energy economics, and using socioeconomic data at Post Code level, the model has the following novel aspects:

- The ANN's ability to improve agent's decision-making process by learning from the agent's past choices via using socioeconomic time series data
- The ABM's ability of characterise the social dynamics at large scale using spatially explicit data sets
- The ANN's capability to capture the evolution of the system using explicit time-horizon

The initial prototype model is developed for the City of Birmingham focusing on the PV adoption process. Our initial auto-regressive model predicts future diffusion patterns at post-code level on a monthly basis. Both limited availability of time series data and spatial influence of other agents' estimations on a given agent's estimation lead to accumulation of errors spatio-temporally (Alderete-Peralta et al., due to submission). Emerging results using socio-economic variables highlight the importance of income, electricity consumption and the household size. We also detect strong spatial dependency in the diffusion patterns.

Overall this work aims to produce novel insights into potential adoption patterns that may help distribution network operators to develop better strategies to accommodate higher loads which will, in turn, help keeping the energy affordable for consumers.

The modelling of agents' behaviour using spatio-temporally explicit data result in more realistic estimation of adoption patterns and provides insights into how adoption patterns might develop in the future in a particular area. Also, the model can be used further to analyse the impacts of alternative policies to influence PV adoption, such as the development of local economic incentives.

2 Methodology

This paper focuses on developing a spatio-temporally explicit ABM, which characterise agents as geographical areas and uses artificial neural networks as the agents' decision-making. The model is structured in two modules: the spatial layout and the decision-making process, the former embedded in the later.

As seen in Figure 1, the spatial layout is an ABM module that defines (i) the agents' characteristics (socioeconomic variables), (ii) agents' location, (iii) agents social-network manages the information flow with the inner module (the agents' states, inputs and outputs). The ANN approach replaces the common rule-based agent's decision-making process such that there are as many neural networks as agents in the simulation.

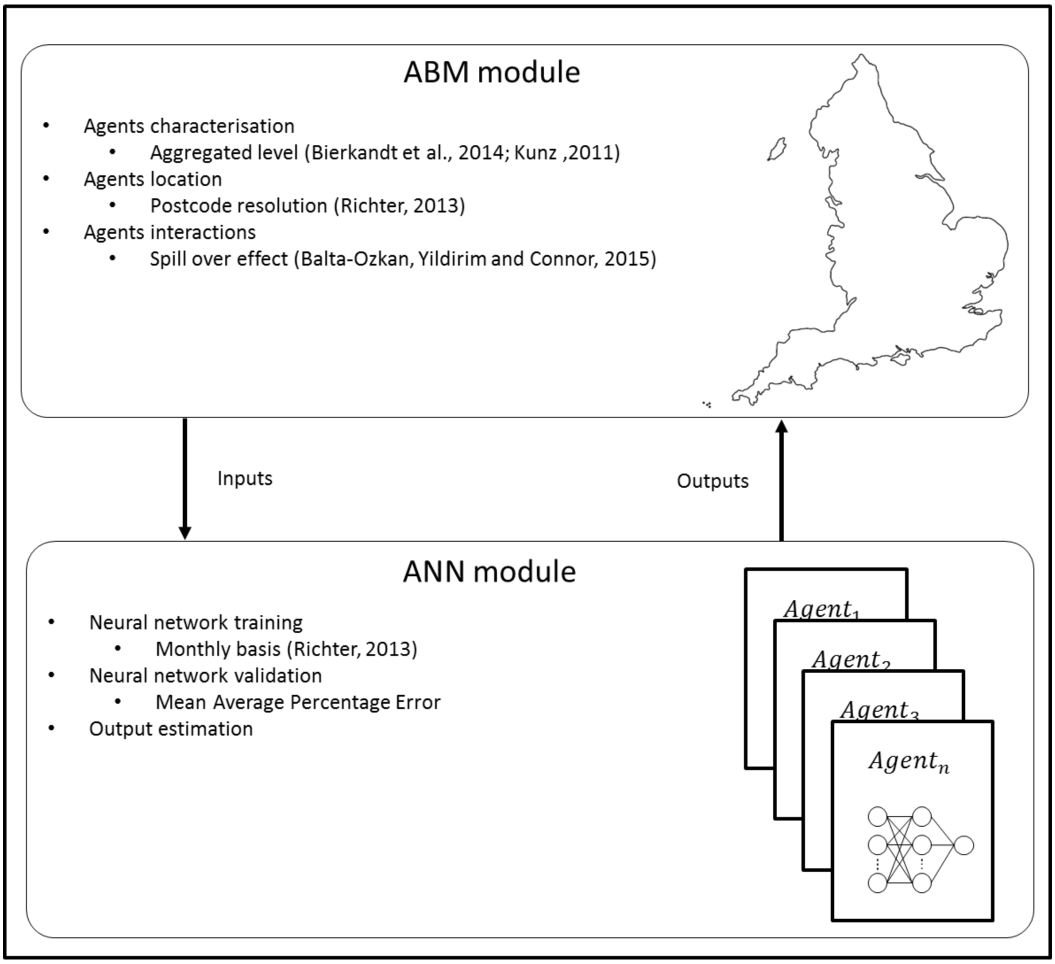

Figure 1. Methodological framework and information flow between the layers.

2.1 ABM module

This work adopts the aggregated definition of agents presented by Bierkandt et al. (2014) and Kunz (2011), characterising the agents as geographical areas. Spatial and temporal resolution follows Richter's (2013) analysis using Postcode districts (PC) and monthly data. The model is empirically tested for the postcode districts in Birmingham city, using time series data on PV registrations by Office of Gas and Electricity Markets (Ofgem).

The social influence is defined by the cumulative number of PV installations in the neighbourhood at any specific month. Following the first law of geography, 'everything is related to everything else, but near things are more related than distant things' (Tobler, 1970, p.236), the social influence is weighted according to the distance between agents. The agents' social network is defined on the adjacency principle where two agents will be connected if they share a boundary. Data correspond to PV installations as of 30 September 2015

Additionally, the model considers other factors affecting the decision-making process that may help to increase the accuracy of the model. Following Balta-Ozkan, Yildirim and Connor's (2015) spatial econometric model, the model considers the following socioeconomic variables: income, population density, share of owned houses, share of detached houses, electricity consumption, education level, average household size, solar irradiation and CO_2 emissions. Figure 2 shows an example of the ABM module where each agent has a fixed position and explicit boundaries. The red lines represent the spill over effect, which is the social effect that spatially adjacent geographical areas have on each other (Balta-Ozkan, Yildirim and Connor, 2015); this effect is affected by the distance between the agents. The blue lines represent the peer effect, which is the social effect that occurs within geographical locations (Richter, 2013)and is not sensitive to the distance.

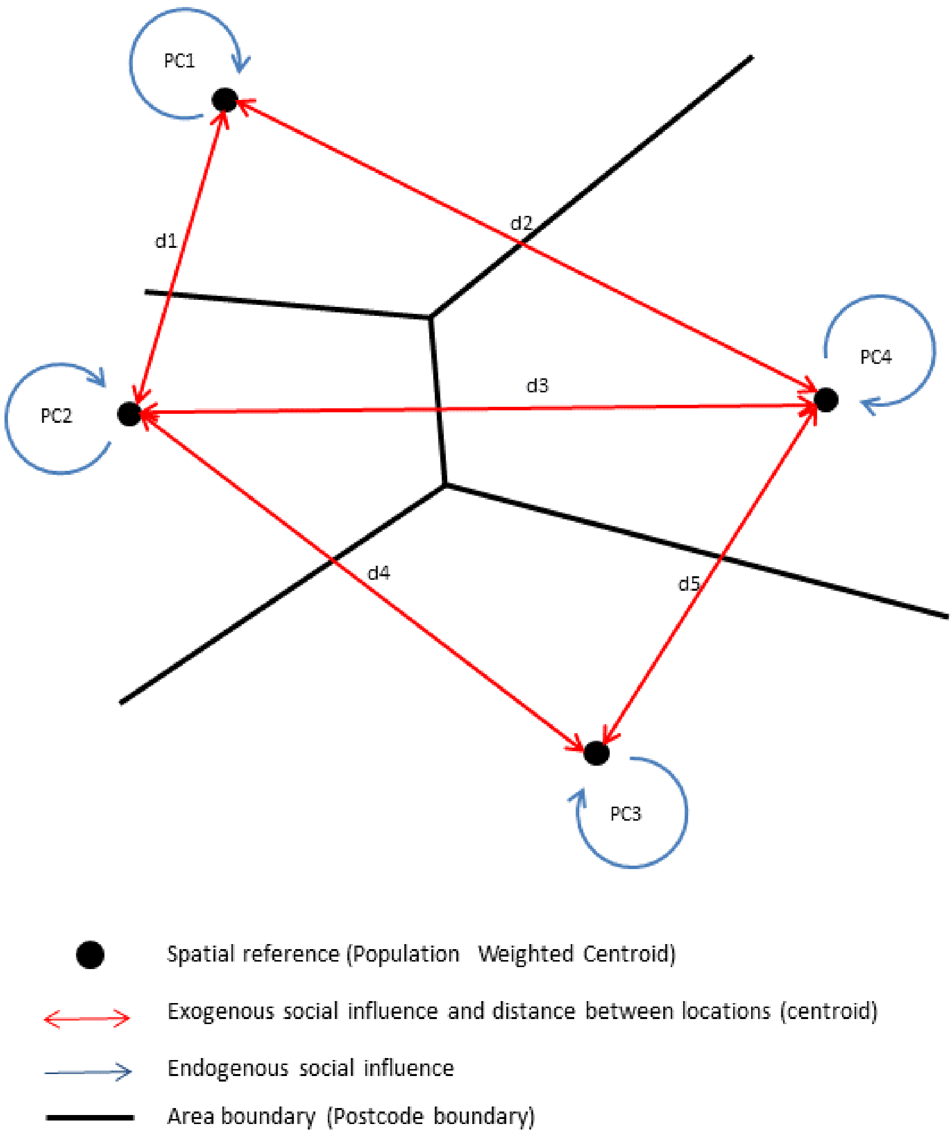

Figure 2. Characterisation of social effects and information flows.

In line with Richter's analysis (Richter, 2013), the study considers total PV installations from 2010 onwards. However, in the case of Birmingham less than 1% of the total PV installations have a registration date before 2011. The examination of the data from 2011 to 2015 results in 72 monthly observations, and a median number of 62. From the Birmingham's PCs, there are three areas with less than five PV installations, contrary to Richter (2013) whose study excluded such areas with minimum or no installations, this study includes these areas as to avoid modifying the spatial layout and the social networks.

2.2 ANN module

This paper focuses on the combination of ABM and ANN to explicitly analyse the spatio-temporal nature of PV adoption process. The ANN's design follows eight-steps identified by Kaastra and Boyd (1996). The authors highlight the following steps which follow a reiterative process: i) Variable selection, ii) Data collection, iii) Data processing, iv) Training, testing, and validation sets, v) Neural network paradigm, iv) Evaluation criteria, vii) Neural network training, and viii) Implementation.

2.2.1 Variable selection

Following Balta-Ozkan, Yildirim and Connor (2015) spatial econometric analysis, the dependent variable is defined as:

$$y = \rho W y + X\beta + \varepsilon$$

Where, the dependent variable (#PVs) is defined by an auto-regressive element, and a set of independent variables. Then, the temporal behaviour is denoted by lagging the inputs, as shown next:

$$PV_{t+1} = f(PV_{t\ local}, IndepVar_{t\ local}, PV_{t\ neighbouring})$$

Initial list of socioeconomic variables follows Balta-Ozkan, Yildirim and Connor's spatial-econometric model (2015), and the final variable's selection is alike the econometric stepwise method, starting with a single variable and selecting the best fit, then introducing a new variable and discretising if it does not improve the fitness, then stopping when the fitness can't be improved any further.

2.2.2 Data collection

Feed-in Tariff Installation Report database is published by the Office of Gas and Electricity Markets (Ofgem), it contains the registered domestic PVs at four spatial references: Country, Local authority, Postcode district and Lower Super Output Area code (LSOA), in monthly basis. Socioeconomic data (census) is published by the Office of National Statistics, containing data such as income or home ownership etc; at aggregated level.

2.2.3 Data processing

This analysis focuses on the analysis of the analysis of PV diffusion patterns at high spatio-temporal resolution, then available data is processed and transformed to fit the model's purpose and requirements. Data at LSOA or MSOA level aggregated to PC level using ONS' reference look up tables. Weekly observations were aggregated to monthly basis, while lower resolution variables were temporal-disaggregated to estimate monthly observations. The only exception is the solar irradiation data because the changes in solar irradiation between one area to another, in this study scope, is minuscule.

As seen in Table 1, half of the variables are available at PC level, the rest of the variables were aggregated from Lower Layer Super Output Area or Medium Layer Super Output Area to Postcode, except for the PV and weekly income temporal resolution that was aggregated or not modified, most of the variables have a low temporal resolution, annual or 10-year timeframe. Consequently, these annual dataset were interpolated into monthly observations following the UK Office of National Statistics' (ONS) methodologies for temporal disaggregation.

Temporal disaggregation is a process for producing a time series at a higher frequency from data with a lower temporal resolution. Following ONS's methodology, the monthly observations were estimated with the Fernandez algorithm. Monthly GDP observations have been estimated from the annual time-series, by applying the Fernandez's technique and using the Index of Services[1] (Chamberlin, 2010). This estimation is at national level using the national level GDP and national index data, then the Index of house pricing was used to substitute the low spatio-temporal resolution index with a high resolution.

Table 1. List of independent socioeconomic variables and their resolution

Variable	**Spatial resolution**	**Temporal resolution**	**Data points**
PV	LSOA	Annual	2011-15
Weekly income	MSOA	Weekly	2013, 2015
Pop. Density	PC	Census	2001,2011
Owned household	PC	Census	2001,2011
Detached household	PC	Census	2001,2011
Electricity consumption	LSOA	Annual	2001, 2011-15
QL2	PC	Census	2010,2015
House household size	PC	Census	2001,2011
CO2	LSOA	Annual	2001,2011

[1] The Index of Services measures the quantity of output from all UK services industries, and accounts for more than three-quarters of the output approach to the measurement of Gross Domestic Product.

2.2.4 Training, testing, and validation sets

ANN generates knowledge through a process of pairing inputs and outputs, then measuring the error between the actual output and the estimation. The ANN is capable to adjust is elements and increases the estimation error. This process takes place in three phases, during the training phase the ANN is feed with a sample of the dependent and independent variables, then one-by-one the estimation error is used to correct the ANN. Then, during the testing a sample of the data is used to determine if the model requires further calibration, if not then during the validation phase a third sample is using to measure the model fitness. Due to the limited number of observations, the sets were split into 90%-5%-5% of the sample, instead of the common 70%-15%-15% of the sample for the training, validation and forecast sets.

2.2.5 Neural network paradigm

Following Babazadeh (2017) ANN design, the input and output nodes represent the independent and dependant variables, respectively. Then the input nodes represent the 1-lag the input variables, $PV_{t\ local}, IndepVar_{t\ local}, PV_{t\ neighbouring},$ and the output node represent the estimation for *t+1*. Figure 3. Example of an artificial neural network .shows an example of an ANN, yellow node represents the inputs (social effects and socioeconomic variables), and red nodes estimate the number of PVs.

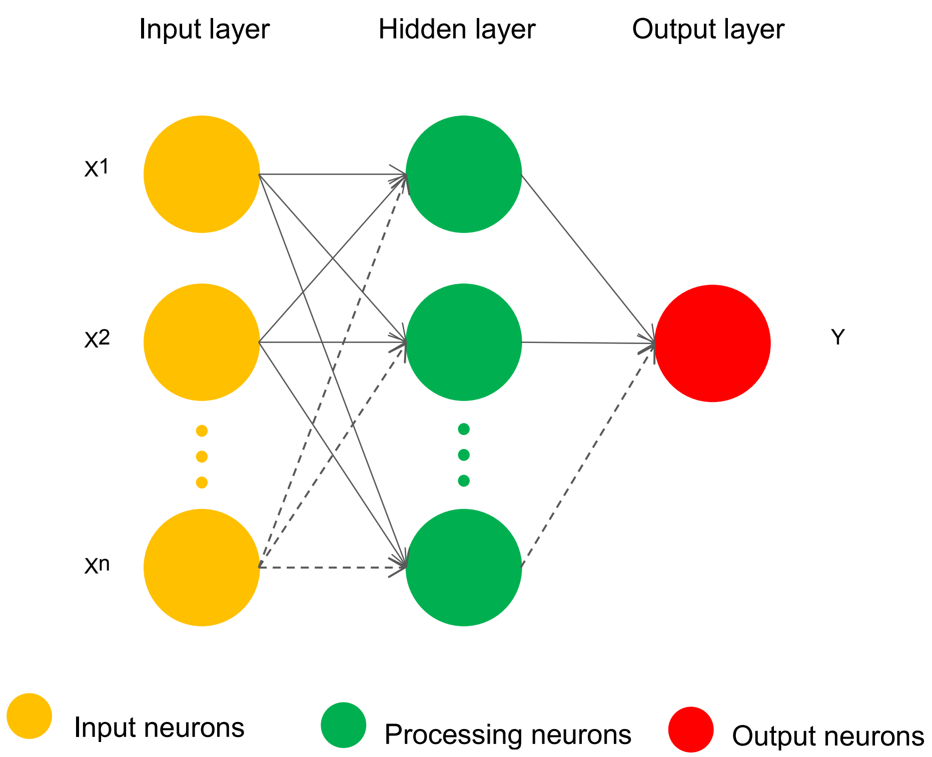

Figure 3. Example of an artificial neural network .

2.2.6 Evaluation criteria

Model was validated temporally and spatially based on the fitness model, this measured using the Mean Average Percentage Error (MAPE). MAPE is a common measure to assess the accuracy of ANN estimation (Samarasinghe, 2016). This was extended to each of the agents' ANN, yielding results for a population of neural networks.

Hence, the model is validated considering the accuracy of the estimation of each neural network, then MAPE evaluation is defined as follows:

$$MAPE_j = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{PV_t - \widehat{PV}_t}{PV_t} \right|$$

Where

n is the time series size

PV_t is the current number of PVs in the month t

$\widehat{PV}_t$ is the estimation of the number of PVs in the month t

i is the specific month

j is the specific area

$$Population\ MAPE = \frac{1}{n}\sum_{i=1}^{n} MAPE_i$$

Where

n is the population size

i is the specific area

2.2.7 Neural network training and Implementation

Each agents' ANN is trained using the back-propagation algorithm, training will take place 5000 iterations or until validation check reaches a square error of 0.0001.

3 Emerging results and discussion

The integrated model empirically characterises 49 agents corresponding to the Birmingham PC districts, agents' variables are updated at each iteration of the simulation. Each of the agent's ANN is feed with its particular time series, reflecting the monthly PV uptake from 2011 to 2015.

Model temporal validation is shown first, average fitness for the entire population in shown over the time. Then, the individual results by PC are mapped, showing their distribution spatially.

3.1 Temporal validation - Model fitness

The model spatial and temporal validation highlights that the income, electricity consumption and average household size are the variables that yield the best fitness, producing a model with a 95% of accuracy. These variables have been proven to drive the adoption process, in both aggregated and individual level. Agent's **income** has been used to define the agents' utility or social threshold (Adepetu, Keshav and Arya, 2016), while aligned with DECC's (2012) reports that suggest that income is a key decision variable for households to adopt the PV technology. **Electricity consumption** and **average household size** follows the same logic, as households with more affluence tend to have a higher electricity consumption. Besides the error introduced by the temporal disaggregation of the socioeconomic data, the results are more realistic as the other models that do not consider changes in the agents' characteristics over time.

Figure 4 shows the average error histogram for the entire population, as the training of the neural networks starts, it is more likely for the neural network to produce extreme values and this presents some disturbances in the first half of the sample. Besides these elements, the MAPE decreases over the time and stabilises at the end of the sample.

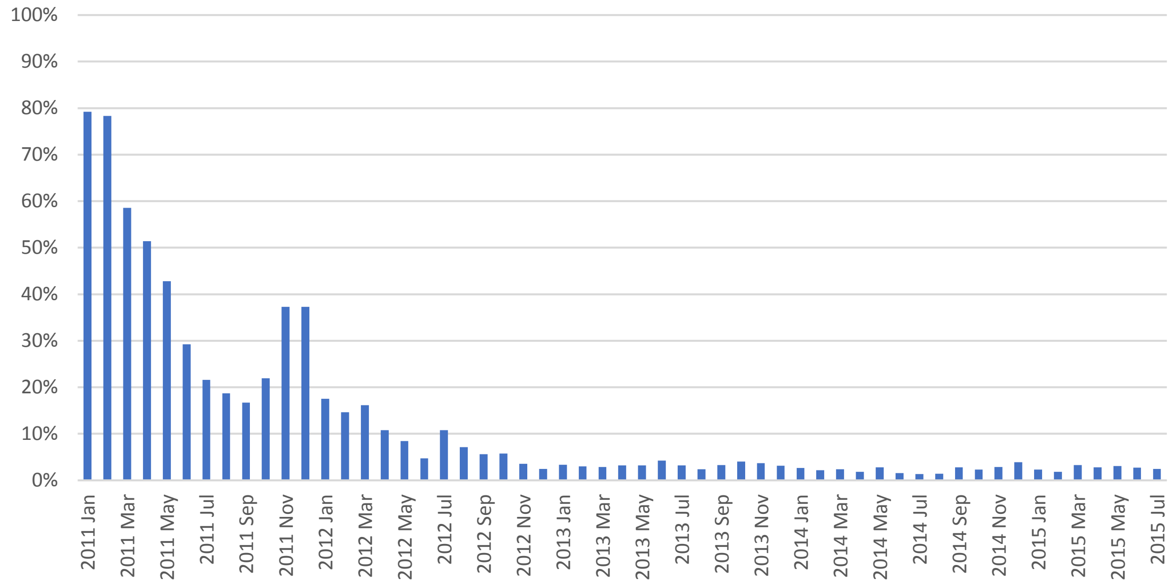

Figure 4. Average Mean Absolute Percentage Error for the entire population over the time (Training phase).

Further analysis of the errors reveals a stronger temporal pattern. The errors' marginal change month by month was calculated and shown in **Figure 5**. Almost 40% of the areas present its largest these disturbances at the end of 2011 (Nov), which corresponds to the highest Feed-in Tariff rate that proceeded to the latter decrement of it. The former is significantly important to the applicability of the model, it shows that the FiT programme doesn't have the same impact on all the areas. The former might suggest that the FiT's efficiency present spatial differences, highlighting the need for more local policies taking into account the emerging spatial patterns.

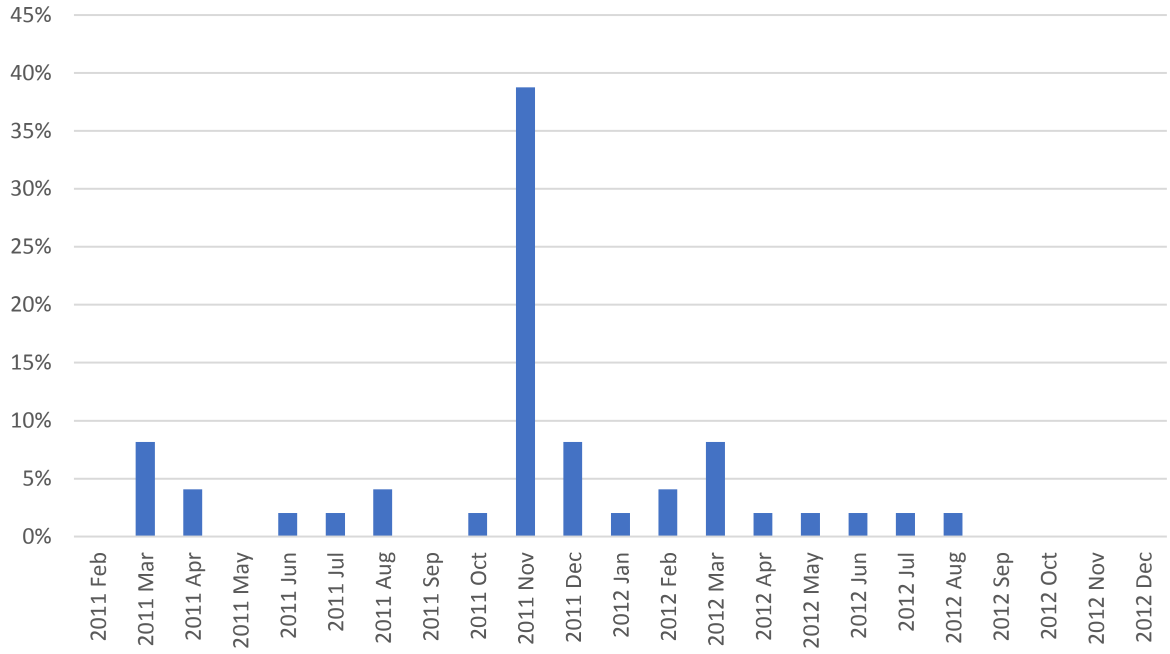

Figure 5. Proportion of the population that at a given point presents a significant change in errors' trends (multivariate model)

3.2 Spatial validation - agent's characterisation

The study focuses on capturing the actual spatial layout of the agents, , thus, this locates agents' accordingly to the Birmingham city layout. The PCs geographical level considers the population size and social homogeneity, providing a more accurate agents' location than the common use of spatial grids (cells) or random location. We argue that taking a spatially explicit approach (in the form of PCs) increases the accuracy and confidence of the model results. Furthermore, contrary to Richter (Richter, 2013) that excludes the areas with a minimum or null number of PVs, our study keeps those to maintain the real-world layout, increasing the authenticity of our results.

Considering the overall results presented in the previous section, the agents' individual results are shown next. As seen in Figure 6, most of the areas present a fitness level above 90%, while the areas with the largest errors (+25%) are the ones with less than five PV installations. Because of the small number of PVs, the MAPE calculation is sensitive to any minor change in estimated value, as in the case of the central PCs in Figure 6 that have the minimum number of PV installations (these cases are coded as

“000”. As seen in Figure 6. and Figure 8. the errors do not follow any spatial pattern, neither the spatial distribution of PV patterns as shown in Figure 7.

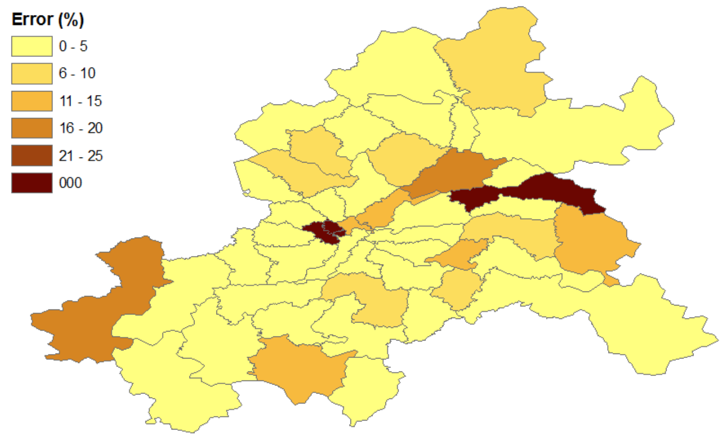

Figure 6. Spatial distribution of error estimation (Mean Absolut Percentage Error) for the Birmingham PCs.

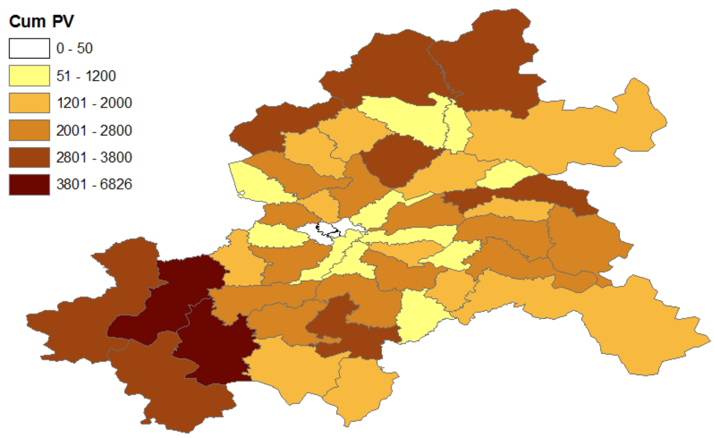

Figure 7. Spatial distribution of the PV installations in the Birmingham PCs.

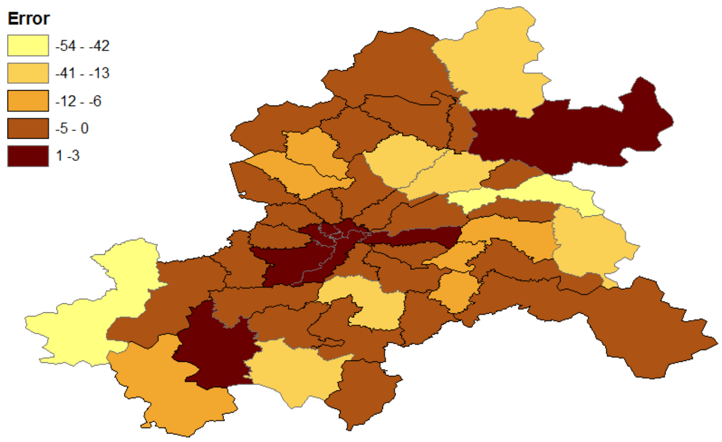

Figure 8. Spatial distribution of error estimation (Absolute error) for the Birmingham PCs.

3.3 Predictive accuracy

Model's forecasting validity was tested excluding 5% of each time-series, after the training process these data was input for the ANN. ANNs were not modified during this process; predictive accuracy follows the same calculation as described in Section 2.2.6. Reversely to the training histogram, as seen in Figure 9, the average forecast's MAPE accumulates. The first forecasted period's error is similar to the training error, but it quickly duplicates to 10% by the fifth step. This is because the estimation is affected not only by the own agent's error, but those of in their social networks.

The PCs individual results for the 1st, 3rd and 5th forecasts are shown in Figure 10, Figure 11, and Figure 12 respectively. During the first forecast period most of the areas have an error below 10%. However, by the fifth forecast the error significantly increases where almost 30% of the agents having more than 10% of errors.

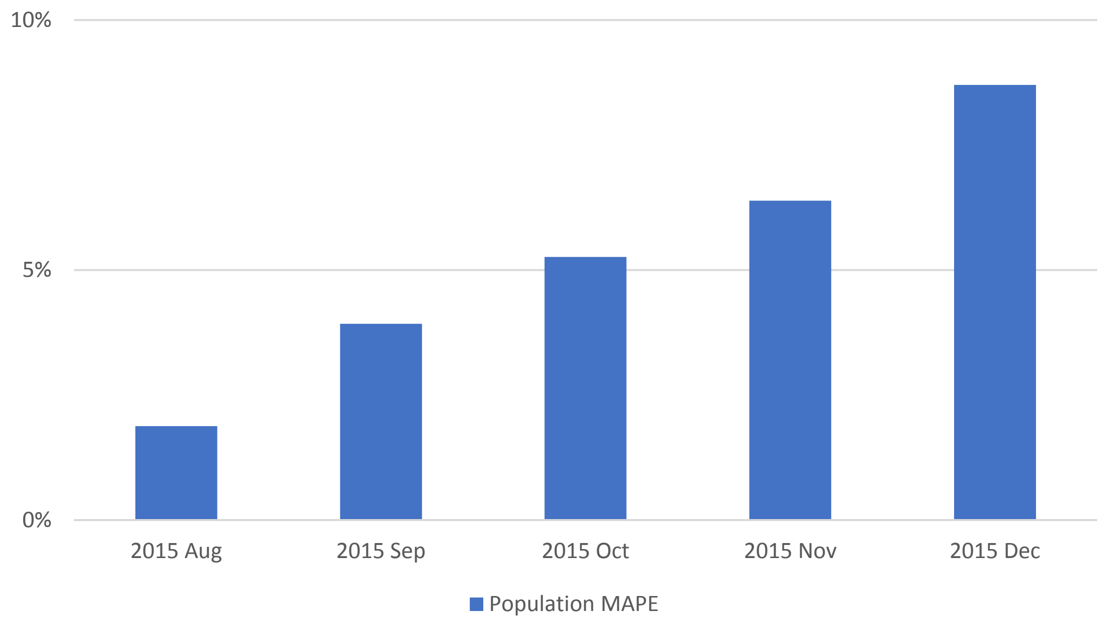

Figure 9. Average Mean Absolute Percentage Error for the entire population over the time.

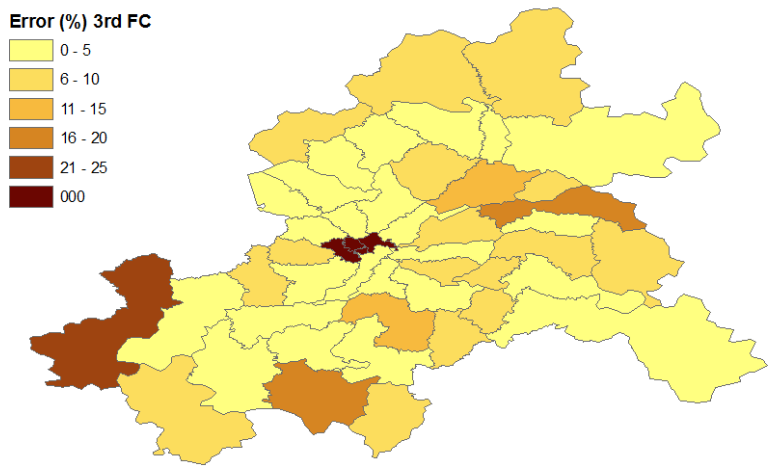

Figure 10. Spatial distribution of error estimation (Mean Absolut Percentage Error) for the Birmingham PCs (3rd forecast).

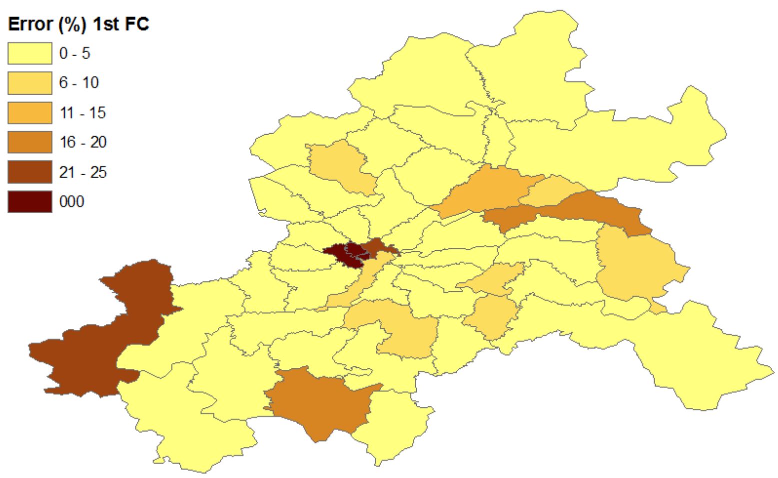

Figure 11. Spatial distribution of error estimation (Mean Absolut Percentage Error) for the Birmingham PCs (1st forecast)

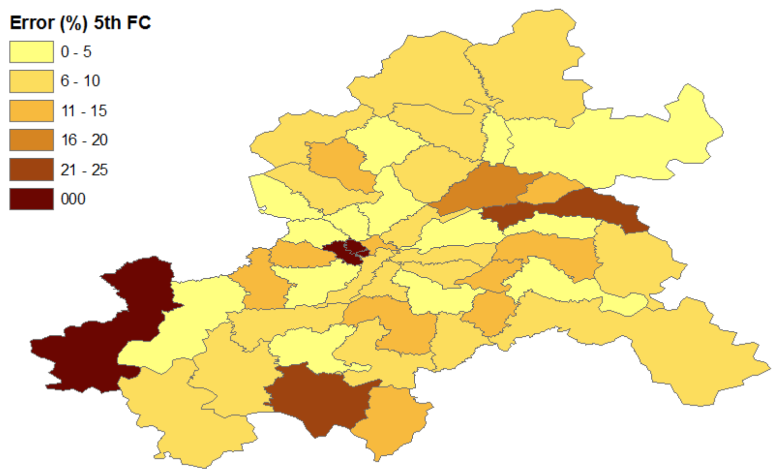

Figure 12. Spatial distribution of error estimation (Mean Absolut Percentage Error) for the Birmingham PCs (5th forecast)

4 Limitations

The limitations of this study and future areas of research are as follows:

- The data processing required for the agents' spatio-temporal characterisation, including temporal disaggregation of socioeconomic variables, may introduce a degree of error into the decision-making process.
- Results presented in this study support the main assumptions of the analysis, however, the results are specific for the city of Birmingham.
- Considering the dynamic nature of agent's characterisation increases the robustness of our results and forecasting,
- As shown in Section 3.2 there is a significant impact of the FiT programme, yet it was not included as an independent variable.

5 Conclusions and future work

This paper presents a novel approach to characterise the PV adoption process at a high temporal and spatial resolution which is empirically validated for the Birmingham city.

The model is capable of estimating future values of the number of PV at postcode district level. This approach can be adopted in any ABM – not only PV ABM.

Furthermore, study advances the study of the PV adoption process, by integrating the ABM the ANN approach into the agent's decision-making process. The ANN approach is validated to be an alternative to the previous decision-making process found in the literature. The most significant improvement carried out by the ANN is the capability to reduce uncertainty by considering the agents' past behaviour.

The model's results consider both the spatial and temporal nature of the process and the social dynamics that drive the adoption process. Hence, the model can complement the findings produced by the aggregated and individual approaches. On the one hand, national studies can analyse the trends but they overlook the spatial dimension. On the other hand, the individual studies are useful to understand the spatial nature of the adoption process, but temporal characterisation is limited.

By addressing these limitations between aggregate and individual studies, the outlined approach integrates the strengths of these approaches. This novel approach reduces the exhaustive data requirements that the individual level approaches require while increasing the certainty of the results. The spatial characterisation increases the degree of certainty on the agent's location, which is fundamental to produce insights on the PV spatial clustering which has important implications for the management of the distribution networks. Hence, the model can produce insights that help distribution network operators to develop better strategies to accommodate higher loads which will, in turn, help keeping the energy affordable for consumers.

Future research might explore extending the study's scope to bigger areas or other cities to assess whether the results are replicated. Extending the time frame by longer statistics but also high-resolution socio-economic data. Additionally, future work could include the FiT variable as an independent variable and confirm its impact on the errors' perturbances shown in this study. Finally, forthcoming work could take advantage and produce more robust insights that helps policy makers in designing local policies that recognise the variation of the socio-economics factors and the financial incentives.

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