Evaluating the contribution of PV to Social, Economic and Environmental Aspects of Community Renewable Energy Projects

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Abstract

For the purpose of the sustainability assessment of distributed renewable energy resources it is desirable to better understand the social, economic and environmental impacts (**SEE**) resulting from their deployment. Often only one, or at most two, of these knowledge domains is considered, partly due to the difficulty of devising an integrated assessment methodology. An approach based on probabilistic graphical models (**PGM**), has been developed which helps address this problem. Data for several UK urban census areas have been systematically collected and processed in order to furnish a PGM with the probabilistic data required in order to simultaneously make inferences about the SEE impacts of domestic solar PV, deployed to high penetrations. Results show that an integrated probabilistic assessment contributes to transdisciplinary knowledge, providing decision makers with a tool to facilitate deliberative and systematic evidence-based policy making incorporating diverse stakeholder perspectives.

Introduction

Renewable energy technologies deployed in community contexts are seen as a valuable contribution to a number of energy policy objectives, and as such are benefitting from a range of financial support mechanisms internationally [1]. In the UK the feed-in-tariff scheme (**FIT**), coupled with rapidly decreasing technology costs, has resulted in rapid diffusion of solar PV within the domestic and community sector. Recently the milestone of 500,000 solar PV installations has been reached [2].

However, significant uncertainty exists with regards to the potential impacts of community scale PV in terms of specific policy goals, including actual (as opposed to projected) greenhouse gas reductions, renewable energy generation capacity and socio-economic benefits such as fuel poverty alleviation. Such uncertainty derives from the wide variability of SEE parameters which characterise solar PV within its deployment context. These uncertainties represent a significant risk for investors and policy makers alike, particularly as their interdependencies are rarely modelled and little understood.

Using a sustainability lens researchers in a number of disciplines have explored the challenges of integrating environmental assessments by developing models which meld socio-economic with environmental factors in order to furnish stakeholders with decision support, diagnostic and simulation tools [3]. Handling uncertainty, both aleatory and epistemic, is a recognised problem when using such methods. Deterministic methods, for example, need to incorporate sensitivity analysis to better measure the variability of output parameters as a function of input parameter variability over a multi-dimensional space. With a large number of parameters this can be difficult and often excludes a consideration of dependencies between inputs.

Latterly PGMs have grown in popularity for modelling problems that require the integration of two or more knowledge domains and which endogenise uncertainty. Model inputs and outputs are intrinsically probabilistic, rendering their variability explicit and their sensitivity to the multi-dimensional parameter space a simple matter of querying the model's joint probability distribution. Specifically, Bayesian Networks (**BN**) can model and integrate knowledge domains in a way found to be intuitive to interdisciplinary researchers and stakeholders [4].

BN are increasingly applied for integrated environmental modelling in ecology and resource management and energy studies. Recently they have been used for modelling optimum carbon mitigation and economic decision making in agriculture [5] and energy scenario studies for a national energy system [6]. The endogenising of uncertainty which allows decision makers to visualise risk as part of a due diligence approach is a distinct advantage of this modelling approach [7].

The match between the largely unquantified uncertainties for integrated assessment of community deployed PV and the methodological benefits of BNs, suggest a number of research questions pertaining to the applicability of this methodology. A key question is: can the use of this approach furnish stakeholders with a decision support or deliberative policy making tools in this problem domain? To explore this, and related questions, a BN has been constructed and is described here. This paper looks briefly at the theory of BNs, the development of a candidate model, and the sourcing and the processing of data with which to encode the dependencies between variables. Finally, some results are explored and discussed in the light of implications for decision support and policy making using this methodology.

Bayesian Networks

A BN is a mathematical model depicted by a directed acyclic graph (**DAG**) where each variable is represented by a node and dependencies between variables are represented by directed edges between them (Figure 1].

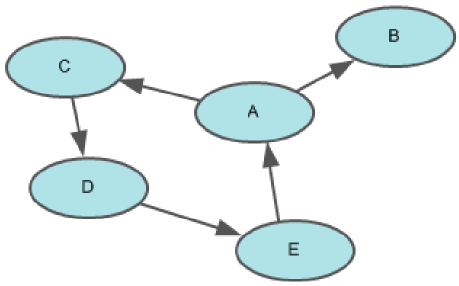


Figure 1. A directed acyclic graph

A root variable has no incoming edges and the corresponding node is encoded with a discretised probability distribution. A child node has one or more incoming edges leading from parent nodes and is encoded with a conditional probability distribution for *each* combination of parent node values. The conditional probability distributions quantify the relationship, causal or observational, between a variable and its parents' variables in the DAG.

This state space can be statistically enumerated using a joint probability distribution (**JPD**), $P(U)$, which provides the probability of each possible combination of every variable in the BN. The semantic of the BN is the independency assumption: each variable of every pair of unconnected variables is independent of the other, given their parent values. The JPD can thus be factorised using the chain rule (Equ. 1). Thus the BN's encoded probability distributions encapsulate the JPD and thereby the entire knowledge domain for which the DAG is a conceptual model.

$$P(U) = \prod_{i=1}^{n} P\big(A_i \big| pa(A_i)\big) \qquad \text{Equ. 1}$$

The utility of this highly compact knowledge representation is further enhanced with reasoning algorithms which propagate evidence - observations on one or more variables - in order to calculate a *posterior* probability distribution of all other variables in the BN [8]. Bayes Rule for conditional probability is used, which given a variable A, calculates the posterior distribution, $P(A|B)$ given evidence B, from the prior distributions, $P(A)$ and $P(B)$ and the likelihood $P(B|A)$ (Equ. 2).

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \qquad \text{Equ. 2}$$

The benefits of a BN are:

I. The efficient storage and encapsulation of an entire knowledge domain.
II. An efficient inference making in both a prognostic sense, when an observation is applied to a root node, or a diagnostic sense when an observation is applied to a leaf node (one with parent but no child nodes)
III. A visual conceptual model in the form of a DAG which is an intuitive causal or influence diagram for the problem domain
IV. The integration of knowledge domains using probabilistic relationships between model parameters to create transdisciplinary knowledge.

*Object Orientated Bayesian Networks (**OOBN**)*

An OOBN consists of a collection of connected BNs, each of which encapsulates a particular knowledge domain [9]. Thus Figure 1 can be reinterpreted such that each object, A,B,C,D and E represents a functioning BN with its own factorised JPD, and the connections represent an interface between output nodes of one network and input nodes of another to enable the transfer of probabilistic information from one network to another.

An OOBN facilitates transdisciplinary enquiry and, particularly for a large network, provides a hierarchical model with each sub-network delivering the benefits listed above. Because of the complexity and multi-disciplinary nature of the problem domain discussed in this paper this was the approach employed in this study. In the next section the knowledge domains which were integrated into a single OOBN are discussed.

Construction of the OOBN

A BN is often constructed using expert knowledge to define the dependencies and independences between the parameters included in the study [10]. An OOBN facilitates this approach and the academic literature was employed to support the DAG structure of each object. Figure 2 presents a UML schema for the model with each titled box representing a network object and the crow-foot connections depicting an interface between the output node of one object and the input of another. Space unfortunately does not permit the displaying of the intra-object connections in this paper.

The evaluation of SEE impacts in domestic and community contexts suggested a focus of the OOBN around defined UK geographic census areas known as a Lower Super Output Area (LSOA). Thus the root BN object was designed to probabilistically characterise the LSOA. The key parameters for which probabilistic data were obtained were the building type, age and floor area (from the Geoinformation Group LTD), the southernmost area, pitch and orientation of roofs from LiDAR data (Bluesky LTD) and modelled household income distributions from census data and the English Housing Survey using an iterative proportional fitting approach [11].

The roof parameters are provided as inputs to the yield object which calculates the specific yield. To calculate this PVGIS was used to provide a modelled yield for every property in the LiDAR dataset. This deterministic value is augmented with an uncertainty parameter calculated from empirical data supplied from the Sheffield Microgeneration database and PVGIS modelled data for the same systems (Figure 3).

Outputs from the Yield and Area objects enable the modelling of a system yield in the PV system object. A building energy demand object was constructed using empirical datasets from the NEED framework [12]. This furnishes the energy cost object with the inputs to provide a probabilistic domestic energy cost. The FiTs subsidy object takes as inputs the energy demand and PV system yields to determine income from export and generation tariffs. To account for self use variability data from the UK solar PV field trials were used to derive the probability distribution which was found to be influenced by both the quantity of PV electricity generated and the total household electricity demand.

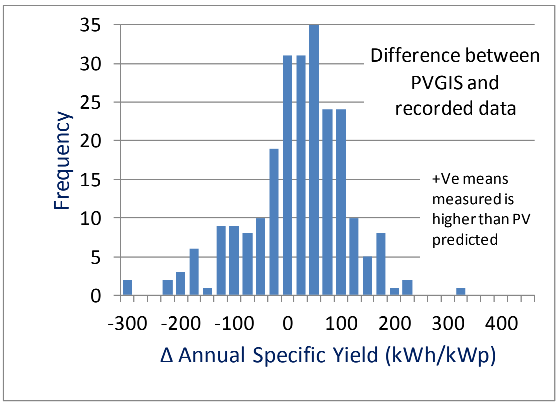


Figure 3 (see text)

The last three objects are used to deliver three SEE indicators; the socio-economic object provides fuel poverty indicators, the NPV object provides a discounted cash flow analysis and the Carbon object provides the carbon savings.

It is worth emphasising that the above brief description masks somewhat the nature of the model's quantitative data. All the parameters have been solicited to furnish

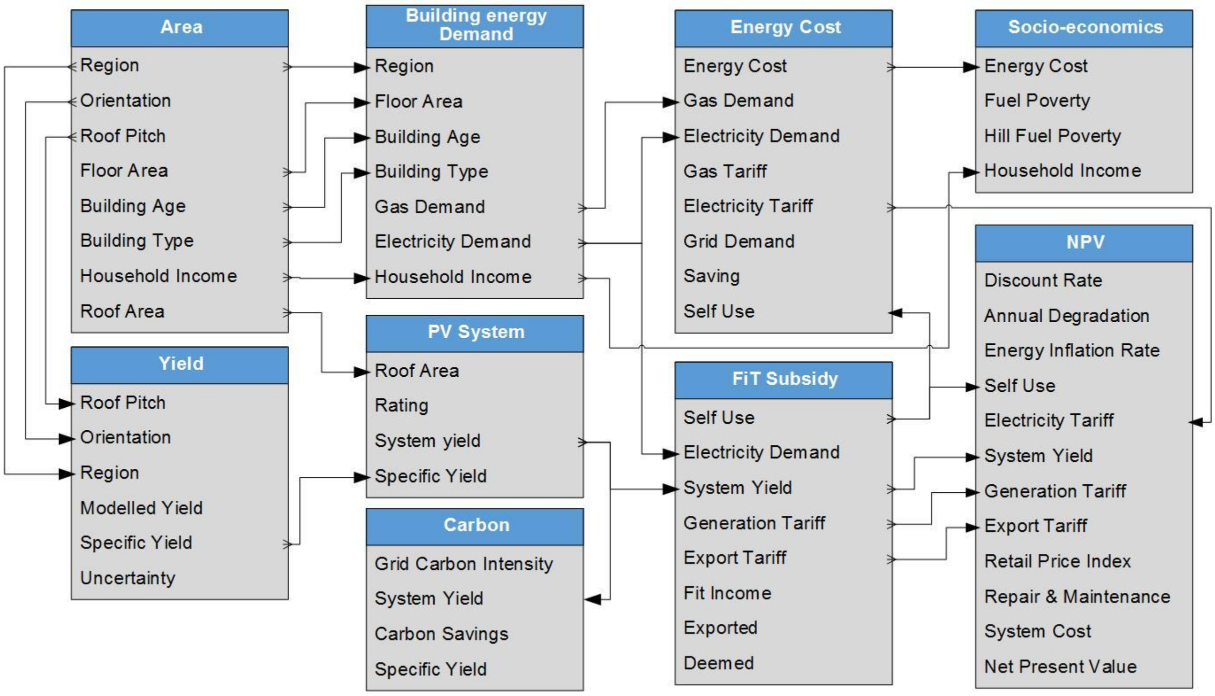


Figure 2. UML diagram of the salient features of the OOBN for solar PV

it with probability mass functions (PMF) - a discretised probability distribution, much as in Figure 3. Furthermore, nodes which have parent nodes have to be encoded with a PMF for each combination of parent values. Thus there is a significant degree of data processing and statistical analysis in order to derive these distributions. Further discussion of all variables, data sources and preparation of PMFs can be found in a forth-coming paper [13].

The OOBN itself was constructed using Netica BN software [14] which allows the simple entering of observations on any node in order to observe the influence of the evidence on all other variables as discussed in the next section.

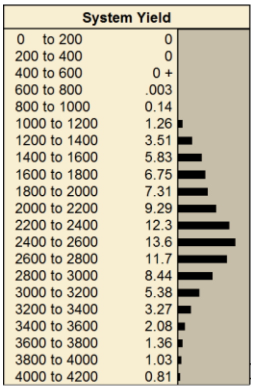
Using the Model and Discussion

The BN imparts an informative prior probability distribution for every variable in the network. The example Figure 3 shows the system yield distribution for an urban LSOA in Loughborough, UK.

The BN offers diagnostic or prognostic utility by fixing one or more specific node values (observations or predictions) and evaluating the resultant posterior - distributions of all other variables of interest.

Of particular interest in this project is the development of a tool to evaluate SEE impacts for distributed renewable energy. Figures 4, 5 and 6 show the distribution of Net Present Value (NPV), carbon emission reductions and the percentage of household income spent on fuel respectively, each with a hypothetical 100% PV penetration.

The model achieves the objective of creating an integrated decision support tool with which a large spectrum of queries can be asked



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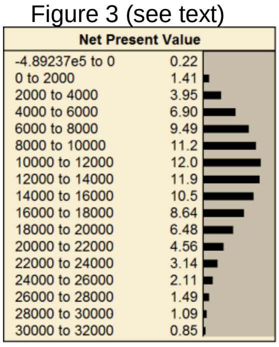

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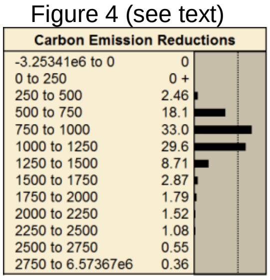

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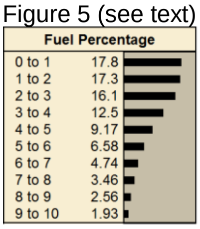

Figure 6 (see text)

and probabilistic answers delivered.

Conclusion

The candidate sustainability indicators provide a valuable multi-criteria parameter set for decision support which can account for diverse stakeholder perspectives. A probabilistic assessment of parameters of interest openly declares the risks pertaining to the attainment of key performance indicators (**KPI**) in a wide number of simulated scenarios using the BN. The prospects of renewable energy acceptance may be improved by deliberative policy and decision making using evidence where uncertainties are transparent. Further work is required to test these hypotheses and to incorporate other KPIs and technologies.

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