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A probabilistic model for 1st stage dimensioning of renewable hydrogen transport micro-economies

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ABSTRACT

The implementation of a hydrogen transport economy based on renewable energy sources is seen by many as the ultimate sustainable transport solution. However, dimensioning of hydrogen production systems is complex: renewable energy sources are stochastic in nature, requiring the collection of empirical datasets relating to weather patterns on a daily, seasonal and annual basis; and hydrogen production is characterised by sensitivity to operating conditions and diversity in the performance of the component parts.

A probabilistic model is developed for dimensioning of hydrogen production systems that removes the reliance on the collection of empirical datasets and the requirement for detailed performance characterisation of component parts. The model utilises well known correlations and distribution modelling techniques to predict energy output from either a photovoltaic array or wind turbine and hence the number of fuel cell electric vehicles (FCEVs) that could be supported on an annual basis.

The model was implemented in MatLab and simulation results were compared with existing empirical based studies. Through simulation, limitations of the model were investigated and discussed. It was shown that the model was able to predict the number of FCEVs supported to within 10% (solar pathway) and 22% (wind pathway) for those studies investigated. These results are in alignment with the intention of the model as a first stage tool for the dimensioning of renewable hydrogen energy transport micro-economies.

1. Introduction

The replacement of hydrocarbon fuels with hydrogen is seen by many as the ultimate transport solution [1]. Hydrogen can be oxidised in an electrochemical reaction within a fuel cell to produce electricity to drive an electric motor. The only emission produced from this reaction is water. Therefore fuel cells electric vehicles (FCEVs) offer emission free propulsion. In addition, the use of fuel cells in electric vehicles offers significantly higher efficiencies than conventional gasoline/diesel systems [2].

Hydrogen molecules (H_2), do not exist naturally, but rather are present as a component of larger molecules, the vast majority of which is water. Hydrogen is an energy carrier (like electricity) rather than a primary fuel source, as there needs to be energy input for it to be produced. There are over 90 identifiable different methods to produce hydrogen over the range of chemical, electrochemical, biological and thermal routes [3]. To ensure a secure, sustainable and environmentally benign transport solution, hydrogen must be produced from renewable energy sources. Technologically and commercially, the most mature of the pathways to renewable hydrogen production is electrolysis using electricity generated from photovoltaic (PV) arrays or wind turbines (WT). However, the production of hydrogen from PV and WT is highly resource dependent and production is likely to be small scale and distributed. Due to the expense of transporting hydrogen, demand will need to be located close to the supply. This will lead to the creation of transport micro-economies [4].

Dimensioning of hydrogen production systems is complex. Renewable energy sources are stochastic in nature, requiring the collection of empirical datasets relating to weather patterns on a daily, seasonal and annual basis, whilst hydrogen production is characterised by operating conditions and a diversity in the performance of the component parts. This study develops a probabilistic model for the purposes of dimensioning hydrogen production systems for hydrogen transport micro-economies. The model looks to remove the reliance on the collection of empirical datasets and

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the requirement for detailed performance characteristics of the component parts. The model was implemented in MatLab and simulation results were compared with existing studies to establish the validity of the model in predicting system size. A parametric study was then undertaken to evaluate the sensitivity of the model results to key input parameters. The model is intended a 1st step assessment tool for developing hydrogen transport micro-economies.

2. Hydrogen system description

2.1. Photovoltaic arrays

A PV cell is a device that converts the energy of sunlight directly into electricity by the photovoltaic effect. In terms of the energy output, the performance of a PV module is tested under standard rated conditions (SRC) of 1000 W/m^2, 25 °C and an air mass (AM) of 1.5 to determine the rated power. Commercial PV cells are available as monocrystalline, polycrystalline and amorphous (thin film) silicon. Due to the structural differences in the silicon between each type of PV cell, each type of construction has different electrical properties resulting in a range of efficiencies. Monocrystalline PV has the highest commercially available conversion efficiency at ~17%, polycrystalline ~12% and amorphous ~8% [5].

The in-service power output from a PV array (PV modules wired together electrically) can be calculated simply from the efficiency and size of the array, and the solar radiation such that:

$$P = \eta_c A G_t \tag{1}$$

where: P is the power output (W); η_c is the efficiency of the array (between 0 and 1); A is the area of the array (m^2); and G_t is the irradiance (W/m^2).

The efficiency η_c of the PV array is strongly influenced by the operating temperature [6]. Increasing cell temperature reduces the cell voltage as the thermally excited electrons increasingly influence the electrical properties of the cell; hence reducing the power output.

PV efficiency modelling has focused on developing relationships for the calculation of operating temperature based on the module type, irradiance and external conditions. A recent review by Skolapi et al. [7] listed 35 separate expressions for operating temperature calculation. These expressions are further subdivided into implicit and explicit expressions. Examples include del Cueto [8] who provides an expression requiring conductive and convective heat transfer coefficients, module emissivity and reflectivity; and Mattei et al. [9] who require a combined front and back heat transfer coefficient as a function of wind speed. These examples highlight the requirement of empirically derived data for many calculations of operating temperature.

For this study a simplified correlation model developed by Skoplaki et al. [10] is used. The derivation of this model is outlined below.

The traditional expression for array efficiency taking into account operating temperature is given as:

$$\eta_c = \eta_{\mathrm{ref}}\left[1 - \beta_{\mathrm{ref}}\left(T_c - T_{\mathrm{ref}}\right)\right] \tag{2}$$

where: η_{ref} is the efficiency at SRC; β_{ref} is the efficiency correction coefficient for temperature (°C^{-1}); T_c is the operating temperature (°C); and T_{ref} is the temperature at SRC (°C).

The value for β_{ref} is dependent on the PV cell material. For polycrystalline silicon cells the value for β_{ref} is taken as 0.0048 °C^{-1} [11]. The value for T_c is largely insensitive to ambient air temperature conditions but highly sensitive to wind speed [12] with convection losses 3–4 times greater than radiation losses [10]. Therefore ignoring radiation and free convection losses from the PV array a simplified relationship can be derived for operating temperature. Substituting typical manufacturer's data for a polycrystalline cell this becomes:

$$T_c = T_a + \left[\frac{0.32}{\left(8.91 + 2.0V_f\right)}\right] G_t \tag{3}$$

where: T_a is the ambient temperature (°C); and V_f is the free wind speed (m/s).

The error associated with the above simplification was calculated by Skoplaki to be less than 2 °C.

Equation (3) assumes that the PV array is free standing, therefore the mounting coefficient, ω, is added. This has been developed from an empirically derived parameter known as the Ross coefficient which modifies the rate of temperature rise above ambient for increasing solar radiation. The Ross coefficient has been calculated for different mounting types and ω is the ratio between them. Values of ω are: free standing $\omega = 1$; flat roof $\omega = 1.2$; sloped roof $\omega = 1.8$; and façade integrated $\omega = 2.4$. Therefore the equation for operating temperature becomes:

$$T_c = T_a + \omega\left[\frac{0.32}{\left(8.91 + 2.0V_f\right)}\right] G_t \tag{4}$$

Combining equations (1), (2) and (4) with $T_{\mathrm{ref}} = 25$ °C (operating temperature at SRC), $\eta_{\mathrm{ref}} = 0.12$ (typical efficiency for a polycrystalline cell at SRC) and $T_a = 15.5$ °C (for the UK and taken from Perry and Hollis [13]) gives the simple correlation for PV array power output based on polycrystalline silicon cells as presented in Skoplaki et al. [10].

$$P = 0.12AG_t\left[1 - 0.0048\left(15.5 + \omega\left[\frac{0.32}{\left(8.91 + 2.0V_f\right)}\right] G_t - 25\right)\right] \tag{5}$$

Though several simplifications have been made in the derivation of the above equation, testing against empirical calculations showed that the average error was 6.5% [10]. It has been shown to be comparable in predicting operating temperature as a function of irradiance to more detailed models. A further advantage of this relationship is that whilst equation (5) commits the user to modelling a polycrystalline silicon cell, it can be easily adapted to other PV technologies by using readily available data.

Solar radiation models have ranged from simple to complex numerical models and have employed a variety of different parameters such as sunshine duration, air temperature, cloudiness, relative humidity, precipitation and atmospheric particle characteristics as inputs. Examples are: Bristow et al. [14] developed a simple mathematical relationship which related the daily total solar radiation to the daily range of air temperature. This model further relied on three empirically derived coefficients which in turn were calculated from measured solar radiation data for the given site. Muneer et al. [15] present a method to calculate direct and diffuse radiation on an hourly basis based on the hourly dry and wet bulb temperatures, atmospheric pressure and sunshine duration. This method proved to be highly accurate for data averaged over a daily or monthly basis with calculated results within 3% of empirically recorded data. Hansen [16] developed a model of daily irradiance calculated from the daily rainfall occurrence and temperature range.

The above methods have primarily been used to complete partial meteorological datasets and hence data such as air