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OPTIMISATION OF STAND-ALONE HYDROGEN-BASED RENEWABLE ENERGY SYSTEMS USING INTELLIGENT TECHNIQUES

by

Adel Z. S. Brka

A thesis with publications presented to Edith Cowan University in fulfilment of the requirement for the degree of Doctor of Philosophy

SCHOOL OF ENGINEERING

FACULTY OF COMPUTING, HEALTH AND SCIENCE

EDITH COWAN UNIVERSITY

December 07, 2015

The declaration page is not included in this version of the thesis

ABSTRACT

Wind and solar irradiance are promising renewable alternatives to fossil fuels due to their availability and topological advantages for local power generation. However, their intermittent and unpredictable nature limits their integration into energy markets. Fortunately, these disadvantages can be partially overcome by using them in combination with energy storage and back-up units. However, the increased complexity of such systems relative to single energy systems makes an optimal sizing method and appropriate Power Management Strategy (PMS) research priorities.

This thesis contributes to the design and integration of stand-alone hybrid renewable energy systems by proposing methodologies to optimise the sizing and operation of hydrogen-based systems. These include using intelligent techniques such as Genetic Algorithm (GA), Particle Swarm Optimisation (PSO) and Neural Networks (NNs). Three design aspects: component sizing; renewables forecasting; and operation coordination, have been investigated. The thesis includes a series of four journal articles.

The first article introduced a multi-objective sizing methodology to optimise standalone, hydrogen-based systems using GA. The sizing method was developed to calculate the optimum capacities of system components that underpin appropriate compromise between investment, renewables penetration and environmental footprint. The system reliability was assessed using the Loss of Power Supply Probability (LPSP) for which a novel modification was introduced to account for load losses during transient start-up times for the back-ups.

The second article investigated the factors that may influence the accuracy of NNs when applied to forecasting short-term renewable energy. That study involved two NNs: Feedforward; and Radial Basis Function in an investigation of the effect of the type, span and resolution of training data, and the length of training pattern, on short-term wind speed prediction accuracy. The impact of forecasting error on estimating the available wind power was also evaluated for a commercially available wind turbine.

The third article experimentally validated the concept of a NN-based (predictive) PMS. A lab-scale (stand-alone) hybrid energy system, which consisted of: an emulated renewable power source; battery bank; and hydrogen fuel cell coupled with metal hydride storage, satisfied the dynamic load demand. The overall power flow of the constructed system was controlled by a NN-based PMS which was implemented using MATLAB and LabVIEW software. The effects of several control parameters, which are either hardware dependent or affect the predictive algorithm, on system performance was investigated under the predictive PMS, this was benchmarked against a rule-based (non-intelligent) strategy.

The fourth article investigated the potential impact of NN-based PMS on the economic and operational characteristics of such hybrid systems. That study benchmarked a rule-based PMS to its (predictive) counterpart. In addition, the effect of real-time fuel cell optimisation using PSO, when applied in the context of predictive PMS was also investigated. The comparative analysis was based on deriving the cost of energy, life cycle emissions, renewables penetration, and duty cycles of fuel cell and electrolyser units. The effects of other parameters such the LPSP level, prediction accuracy were also investigated.

The developed techniques outperformed traditional approaches by drawing upon complex artificial intelligence models. The research could underpin cost-effective, reliable power supplies to remote communities as well as reducing the dependence on fossil fuels and the associated environmental footprint.

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Completion of this Doctoral research would not have been possible without the support of many people throughout my candidature as a student at Edith Cowan University (ECU). I would like to thank my principal supervisor, Dr Ganesh Kothapalli, and Coprincipal Dr Yasir Al-Abdeli. Their support, provided to me throughout the duration of the research project has been invaluable.

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LIST OF SYMBOLS

APE	Absolute percentage error
В	Atmospheric extinction coefficient
B _{SOC}	Battery state of charge
B _{min}	Minimum battery state of charge
B _{max}	Maximum battery state of charge
С	Sky diffusion factor
C _{cap}	Capital cost per unit
C _{rep}	Replacement cost per unit
$C_{o\&m}$	Operation and maintenance cost per unit
CRF	Capital recovery factor
C_{H_2}	Hydrogen conversion coefficient,
<i>E</i> _{<i>H</i>2,0}	Initial energy of hydrogen storage
E _{H2}	Energy of hydrogen storage
E _{H2,max}	Maximum energy capacity of hydrogen storage
E _{bat,0}	Initial energy of battery
E _{bat}	Battery energy
E _{bat,max}	Maximum energy of battery
EE	Excess energy
E _i	Energy converted or stored by components
E_g	Bandgap energy
Error	Prediction error

F_j^{min}	Minimum value of the j^{th} objective function
F_j^{max}	Maximum value of the j^{th} objective function
F	Value of the objective function
H _{SOC,end}	Hydrogen storage state of charge at the end of the year
H _{SOC,initial}	Initial hydrogen storage state of charge
Н	Wind turbine hub height
H ₀	Reference height
H _{SOC}	Hydrogen storage state of charge
H _{min}	Minimum hydrogen storage state of charge
H _{max}	Maximum hydrogen storage state of charge
I _{mp}	Maximum power point current
I _{SC}	Nominal short circuit current
I_{PV}	Solar-PV current
I_{ph}	Photon current
I _{sat}	Diode reverse's saturation current
I _{sat,0}	Nominal saturation current
I _{ele}	Electrolyser current
I _{bat}	Battery current
Ι	Hourly global solar irradiance
I_N	Hourly beam irradiance and the
I _d	Hourly diffusion radiation
Κ	Boltzmann constant
K _i	Single payment present worth

LPSP _{common}	Common loss of load probability index
$LPS_{FC_nominal}$	Loss of power supply when fuel cells transients ignored
LPSP _{modefied}	Modified loss of power supply probability index
LPS _{transients}	Loss of power supply during fuel cell transients
LCE	Life cycle emissions
L _i	Component lifetime
MAPE	Mean absolute percentage error
М	Number of non-dominated solutions
N _{obj}	Number of objective functions
N _{i,min}	Minimum allowable number of units
N _{i,max}	Maximum allowable number of units
NPC	Net present cost
N _i	Number of units
P_e, \hat{P}_e	Measured and predicted load demand
P_{Load}, \hat{P}_{Load}	Measured and predicted load demand
$P_{primary}, \hat{P}_{primary}$	Measured and predicted output power form the primary source
P _{ren}	Renewable power
P _{bat}	The output power of the battery
$P_{B_Discharge}$	Maximum battery discharge power
P_{B_Charge}	Maximum battery charge power
P _{in,inv}	Inverter input power
P _{inv,Load}	Inverter output power
P _{EL,max}	Electrolyser maximum power

P _{FC}	Fuel cell power
P _{exc}	Excess power
<i>Q_{max}</i>	Battery maximum capacity
R_S	Series resistance
R_P	Shunt resistance
R	System's lifetime
T_{op}	Operation temperature
V _{PV}	Solar-PV voltage
V _t	Thermal voltage
V _{mp}	Maximum power point voltage
V _{oc}	Nominal open circuit voltage
\dot{V}_{EL}	Electrolyser hydrogen production rate
\dot{V}_{FC}	Fuel cell hydrogen consumption rate
V _T	Conversion constant
V _{bat}	Battery voltage
V _b	Battery terminal voltage
V _{con}	Battery constant voltage
V _{t,n}	Thermal voltage at the nominal temperature
С	Centre of Gaussian function
i _{FC}	Fuel cell current
ir	Monetary interest rate
n _c	Number of electrolyser cells
q	Electron charge

r	Spinning reserve factor
ν	Wind speed
v_0	Wind speed at a reference height
W _{kj}	Neuron connection weight
y_p	p^{th} input pattern of the neural network
у	Measured value
ŷ	Predicated value
y_i	Number of component replacements during the project lifetime
Ζ	Weighted sum of neuron inputs
δ	Mean square deviation of the Gaussian function
Δt	Time interval
$ au_{FC}$	Fuel cell transient time
α	Wind shear exponent coefficient
μ_{EL}	Electrolyser efficiency
ΔH	Hydrogen enthalpy
μ_{inv}	Inverter efficiency
β_i	Equivalent CO ₂ emission over the lifetime of a component
μ_j	Fuzzy membership function value for the j^{th} objective function
μ^k	Normalised fuzzy membership function
x	Slope parameter of sigmoid function
θ_Z	Zenith angle

LIST OF ACRONYMS

ABSO	Artificial bee swarm optimization
AFC	Alkaline fuel cell
ARMA	Auto-Regressive Moving Average
BAT	Battery
COE	Cost of energy
DFIG	Doubly Fed Induction Generator
DLL	Dynamic Link Library
ELC	Electrolyser
FC	Fuel Cell
FL	Fuzzy logic
GA	Genetic algorithm
H2	Hydrogen
HS	Harmony search
IEA	International energy agency
INV	Inverter
LOEE	Loss of Energy Expected
LOLE	Loss of Load Expected
LOLP	Loss of Load Probability
LOLH	Loss of Load Hours
LCC	Life Cycle Cost (LCC)
LCE	Life cycle emissions
LPSP	Loss of Power Supply Probability

LCOE	Levelised Cost of Energy
LTP	Length of Training Pattern
MCFC	Molten carbonate fuel cell
NN	Neural Network
NPC	Net Present Cost
NWP	Numerical Weather Prediction
OP-PMS	Optimised Predictive Power Management Strategy
PMS	Power Management Strategy
PMSG	Permanent Magnet Synchronous Generator
PV	Photovoltaic
PEMFC	Proton exchange membrane fuel cell
PAFC	Phosphoric acid fuel cell
PSO	Particle swarm optimization
P-PMS	Predictive Power Management Strategy
R-PMS	Reactive Power Management Strategy
SG	Synchronous Generator
SOFC	Solid oxide fuel cell
SPL	System Performance Level
SCIG	Squirrel Cage rotor Induction Generator
SA	Simulated annealing
TS	Tabu search
WECS	Wind energy conversion system
WG	Wind Turbine
WRIG	Wound Rotor Induction Generator xii

LIST OF PUBLICATIONS

Published Journal Papers

- A. Brka, Y. M. Al-Abdeli, and G. Kothapalli, "The interplay between renewables penetration, costing and emissions in the sizing of stand-alone hydrogen systems," International Journal of Hydrogen Energy, vol. 40, pp. 125-135, 2015. <u>http://www.sciencedirect.com/science/article/pii/S0360319914030080</u>
- A. Brka, Y. M. Al-Abdeli, and G. Kothapalli, "Influence of neural network training parameters on short-term wind forecasting," International Journal of Sustainable Energy, vol. 35, pp. 115-131, 2016. <u>http://www.tandfonline.com/doi/abs/10.1080/14786451.2013.873437#.VZ1kM_mqqko</u>
- A. Brka, G. Kothapalli and Y. M. Al-Abdeli, "Predictive power management strategies for stand-alone hydrogen systems: Lab-scale validation," International Journal of Hydrogen Energy, vol. 40, pp. 9907-9916, 2015. doi:10.1016/j.ijhydene.2015.06.081 <u>http://www.sciencedirect.com/science/article/pii/S0360319915015669</u>

Papers under review

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Conference Papers

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1 CHAPTER 1: GENERAL INTRODUCTION

1.1 BACKGROUND

Energy is an essential part of modern life. By converting it into different forms, energy sources help power all the important utilities, such as electricity and water. In the past century, the rapid increase in the world's population plus a high standard of quality of life has increased global energy demand and it is expected to grow even faster and more significantly in the near future. To secure continuous energy supply, the world depends mostly on the use and existence of fossil fuels. Since electricity is the most common energy carrier, a considerable part of energy resources is used to generate electricity. According to the International Energy Agency (IEA), in 2012 fossil fuels were used to generate more than 67% of total electricity (Figure 1-1) [1]. The remaining electricity generation comes from hydro, nuclear and renewable energies. The projections for the future energy demand of most nations in the world show that economic growth is highly dependent on whether the ever-increasing energy demand can be met. The Australian electricity demand is projected to grow from 180,390 gigawatt hours (GWh) in 2014–15 to 192,131 GWh in 2017–18, an average annual increase of 2.1% [2].





[1].

The electricity demand is generated mainly by thermal power plants that use fossil fuels such as coal, natural gas and oil. Australia relies more heavily on coal for electricity generation than global and Organization for Economic Co-operation and Development (OECD) averages [3]. Australia has 9% of the world's black coal reserves and 80% of the nation's electricity demand is generated by coal-fired power stations [3]. Owing to its low price and relatively abundant reserves, it is expected that coal will continue to be the main electricity generation source, regardless of the pressure to reduce greenhouse gas and other air-pollutant emissions. Natural gas power-generation technology is another option for electricity generation because of its operation flexibility, fuel efficiency and lower installation costs compared to other conventional generation technologies. Oil is not a major source for electric power because the major petroleum products are used mainly for transportation purposes, such as car fuel and aviation fuel. While the demand for oil keeps increasing, the shortage and uneven distribution of its reserves are some of the major problems for using oil as a power source.

Electricity can be generated by technologies other than the widely used ones mentioned above; for example, nuclear, hydropower energy. Nuclear energy is an important source of electricity generation in many developed countries, but the contribution of nuclear energy to the world's electricity generation is very small because of the limitations on the access of nuclear technology for emerging and developing nations, concerns about the safety of nuclear power plants and the environmental impact of nuclear waste. In addition, public perception of nuclear energy has changed after the severe and long-term damage that happened because of the Chernobyl disaster (1986), and the Japanese nuclear plant catastrophe (2011) [4].

Nowadays, hydropower is the largest renewable source for electricity generation in the world. In 2012, more than 16% of the world electricity was supplied by hydropower, and this percentage is expected to grow slightly owing to large hydropower electricity generation projects in the regions with emerging economies. Although hydropower is clean and renewable, there are some negative and unavoidable environmental and social side effects resulting from the dams and reservoirs needed to build the hydropower plants. In addition, hydropower is not as abundant as other renewable energy sources. Alternative power generating technologies such as wind generators, solar-photovoltaic (solar-PV) panels, fuel cells, biomass power plants and, geothermal power stations have also been used for electricity generation, but the contributions of these technologies to the total world's electricity generation is relatively small. In

Australia, for instance, statistics show that renewable energy provided only 14.76% of the nation's electricity demand in 2013 [5]. The main reason is that renewable power plants are more costly to build compared to traditional power stations.

The dependence on fossil fuels as the main energy source comes with major negative effects. Fossil fuel resources are finite and are not distributed evenly around the world. As a result, the price of these resources is continuously increasing as they are depleted, as well as a result of coincidental geopolitical factors which, in turn, affect the long-term energy security of many nations. Moreover, the emissions resulting from fossil fuels have a negative effect on the environment, with the result that both climate change and increases in world temperature are believed to be a result of the extensive use of fossil fuels. All the aforementioned drawbacks have increased awareness of the environmental impact of using fossil fuels and the risks associated with nuclear energy. These have motivated the attempts to develop electricity generation technologies that use sustainable and environmentally friendly energy resources.

1.2 ALTERNATIVE POWER GENERATION

Alternative energy and renewable energy are often used interchangeably to refer to energy resources that are replenished naturally and can be used to generate power in an environmentally friendly way. There is a broad range of energy resources that can be classified as a renewables, such as wind, solar irradiance, hydrogen, biomass and geothermal energy. Although the majority of the world electricity nowadays is still generated by conventional power sources, many nations are moving towards reducing the dependence on fossil fuels by using alternative energy resources for electricity generation. The main motivations are the cost of non-renewably generated electricity and the environmental impact of fossil fuels. According to the US Energy Information Administration, the world crude oil price has increased from around \$18 per barrel in 1987 to \$114 in 2014 [6]. Since fossil fuels are not renewable, it is expected that the price of these fuels will rise as the world reserves are depleted. Coal and natural gas are relatively cheaper than crude oil. However, the cost of electricity generated by these two sources would be much higher if the cost for reducing emissions were taken into account. On the other hand, alternative energy resources are not only renewable but also abundant. For instance, the earth's surface receives around 100 times more solar energy than the all fossil consumption [7]. Moreover, some renewable resources such as wind and solar energy are available almost everywhere, which allows the installation of renewable power-generation systems close to load centres, thus avoiding costly energy transmission lines, which may exceed \$AU 1 million per kilometre [8], to

3

connect loads to centralised power-generation plants. This also makes renewable power systems suitable for supplying electricity to isolated inhabited areas, where there is no access to a large-scale public grid for electric power. Finally, unlike fossil fuels, renewables have no negative environmental impacts and no disposal costs are associated with them [7].

In general, alternative/renewable power-generation systems have recently attracted increased interest because they are abundant, environmentally friendly and have modular structure, which make them very good candidates to improve energy security for nations that have no, or limited fossil fuel reserves.

1.3 RENEWABLE ENERGY TECHNOLOGIES

1.3.1 Wind energy conversion system

The Wind Energy Conversion System (WECS) converts kinetic energy of the wind speed into electrical energy. Typically, a WECS consists of wind turbine blades, an electric generator, a power-conditioning and a control system. Different configurations of WECS are available based on the electrical generator used (synchronous or asynchronous), and the power-regulation mechanism employed (stall-regulated or pitch-regulated). The wind turbines can be classified according to the orientation of the rotors into vertical axis wind turbines and horizontal axis wind turbines as shown in Figure 1-2 [9]. Vertical axis wind turbines use a simple and low-cost blade design. Also, they are easy to maintain because the generator and gearbox are mounted on the ground. In addition, they require no yaw control because the wind can be received from any direction. However, this type has some disadvantages, such as low efficiency, difficulty in controlling blade over-speed and high oscillatory components in the aerodynamic torque [10, 11]. The horizontal axis wind turbine is mounted on a tower, in order to receive stronger winds. They are more efficient compared to vertical axis ones, and have lower cost-to power ratio but their design is more complex and more difficult to maintain, because the generator and gearbox are mounted on a tower [11].



Figure 1-2: Typical vertical axis and horizontal axis wind turbines [12].

The generator converts the mechanical torque from the wind rotor to electrical power. Different types of generators are used with wind turbines. DC generators of up to a few kilowatts in capacity are usually used with small wind turbines, while three-phase AC generators are used with modern wind turbines. Several types of AC generators are used with wind turbines including a Squirrel Cage rotor Induction Generator (SCIG), a Wound Rotor Induction Generator (WRIG), a Doubly Fed Induction Generator (DFIG), a Synchronous Generator (SG) and a Permanent Magnet Synchronous Generator (PMSG). The SCIG and WRIG are popular in commercial wind turbines because of their low price, robust structure, mechanical simplicity and resistance to disturbance and vibration [13]. The design of the DFIG allows it to operate at variable speeds with small and cheap converters [14], while the SG is favourable with respect to lifetime and maintenance, because it is connected directly to wind turbines with no gearbox [15]. In the PMSG, the magnetisation of the generator windings is provided by a permanent magnet pole system or DC supply. This feature provides a self-excitation property to the generator, which allows it to operate at high power factors and high efficiencies. The gearbox mechanically connects the wind turbine's rotor and the electrical generator, and allows matching the generator speed to that of the turbine's rotor.

However, the WECS with a gearbox is less efficient and, in some cases, less reliable [11].

Beside the aforementioned main components, speed controllers are used with modern WECSs. The speed controlling methods are usually divided into constant-speed control and variable-speed control. Although the constant-speed control is easier to implement, variable-speed control has many more advantages, including reducing acoustical noise at lower wind speeds, minimising mechanical stress and reducing variations in the generated electrical power [16-18]. In addition, WECSs with variable-speed control use power converters to change the variable-amplitude and variable-frequency power resulting from the AC generator into constant-frequency and constant-amplitude power which can be used by useful loads, and attain maximum power transfer from the wind turbine to the load [19].

1.3.1.1 Modelling wind energy conversion system

In order to analyse performance and estimate the output power of wind turbines, different mathematical models of WECSs have been developed in the literature [20-22]. The operational performance of the wind turbine is usually modelled numerically using the following commonly used aerodynamic equation [11]:

1.1

$$E_k = 0.5mv^2$$

where v is the wind speed and m is the mass of air passing the turbine blades at time period t, given by:

$$m = \rho A v t \tag{1.2}$$

In this regard, ρ is the air density (kg/m³) and *A* is the swept area of the blades. Based on the above equations, wind power can be expressed as follows:

$$P_W = 0.5\rho A v^3 \tag{1.3}$$

From this equation, it can be observed that the specific power of the wind is proportional to the cube of the wind speed. However, the actual power extracted by the wind turbine from the wind is less than the available power, and proportional to the difference between the upstream wind speed, v, at the entrance of the wind turbine's rotor, and the downstream wind speed, v_0 , at the exit of the rotor according to the following formula:

$$P = 0.5K_m(v^2 - v_0^2)$$
 1.4

The variable K_m represents the mass flow rate and can be expressed as:

$$K_m = \rho A \, (v + v_0) / 2 \tag{1.5}$$

From equations 1.3 and 1.4, the mechanical power extracted by the turbine is given by:

$$= 0.5\rho A v^3 C_p \tag{1.6}$$

Р

where $C_p = 0.5(1 + v_0/v)[(1 - v_0/v)^2]$ is the power coefficient of the wind turbine and has a theoretical maximum value of 0.59, but in practice its value ranges between 0.4 and 0.5 [23]. In relation to the electrical generators, the Thevenin equivalent circuit model [24] and *d*, *q* model [25] are commonly used to study the dynamic performance of induction and PMSG generators respectively. However, the aforementioned models are computationally expensive. To reduce the computational cost, other models, based on the polynomial fitting of the practical characteristic curves of the wind turbines, such as the one shown in Figure 1-3, are widely used in the literature [26, 27]. These types of wind turbine models can be represented by equation **1.7** where the values of v_{cut-in} and $v_{cut-out}$ are usually provided by manufacturers.



Figure 1-3: Power-vs-wind speed curve of 2kW off-grid wind turbine [28].

Since wind speed near to ground changes with height according to the power law and as wind power is proportional to the cube of wind speed, the hub height has a great influence on the output of the wind turbine. Therefore, the wind-speed data should be converted to their corresponding values at the hub height when calculating the output of the wind turbine [29].

1.3.2 Solar-PV panels

The photovoltaic effect is a basic physical process through which solar energy is converted into electrical energy directly. The structure of a basic solar-PV cell, illustrated in Figure 1-4, is similar to a classical bipolar p-n junction diode [23]. When a solar-PV cell receives solar irradiance, the photon energy frees electrons from the semiconductor material which results in the creation of electron-hole pairs. The generated electrons are then dragged by the electric field through an external circuit to provide the electrical power to a load. Generally, there are two types of solar-PV cells, namely: non-concentrating and concentrating cells. The Non-concentrating solar-PV cells usually have the same interception and absorption area whereas concentrating solar-PV cells usually have concave reflecting surfaces to receive and concentrate solar irradiance to smaller areas, in order to get higher radiation flux. A solar-PV panel is formed by connecting several individual cells in series.



Figure 1-4: Block diagram of a basic solar-PV cell [30].

1.3.2.1 Modelling solar-PV panels

A mathematical model of a solar-PV panel is useful in studying the behaviour of solar panels under different conditions of solar irradiation and temperature. It is also helpful in estimating the output power and studying the maximum power point-tracking algorithms of solar energy systems. The basic equation that describes the current-voltage characteristics of an ideal single solar-PV cell is [31]:

$$I_{PV} = I_{ph} - I_{sat} \left[exp^{\frac{V_{PV} + R_s I_{PV}}{V_t}} - 1 \right]$$
 1.8

where, I_{ph} is the current generated by incident solar irradiance, I_{sat} is the reverse saturation current of the diode, $V_t = KT_{op}/q$ is the thermal voltage (Boltzmann

constant, $K = 1.38 \times 10^{-23}$; T_{op} is the operation temperature of the p - n junction and electron charge, $q = 1.6 \times 10^{-19}$) and R_s is the forward resistance of the junction. Figure 1-5 shows a diagram of a single-diode model of a practical solar-PV cell.



Figure 1-5: Single-diode model of practical solar-PV cell.

As shown in Figure 1-5, a practical solar-PV cell includes a shunt resister, R_P , in addition to the series resistor. To represent the practical solar-PV cell, additional parameters that take into account the effect of shunt resistor should be included into equation 1.8. The following equation represents the current-voltage characteristics of a practical solar-PV cell [31, 32].

$$I_{PV} = I_{ph} - I_{sat} \left[exp^{\frac{V_{PV} + R_s I_{PV}}{V_t}} - 1 \right] - (V_{PV} + R_s I_{PV})/R_P$$
 1.9

The parameters of equation 1.9 can be determined using the data provided by the solar-PV panel manufacturers. Datasheets provided by the manufactures usually provide the following information: maximum output power, P_{max} ; nominal short-circuit current, I_{SC} ; nominal open-circuit voltage, V_{OC} ; maximum power point voltage, V_{mp} ; maximum power point current, I_{mp} ; open-circuit voltage-temperature coefficient, K_V ; and the short-circuit current-temperature coefficient, K_I . These parameters are usually calculated under standard test conditions for temperature and solar irradiance. Apart from resisters, the required parameters can be retrieved directly from the datasheet. The effect of $(V + I_{PV}R_S)/R_P$ is very small compared with I_{ph} , and determining the value of the shunt resister R_P involves iterative numerical calculations. Therefore, the shunt resister on the current-voltage characteristics of solar-PV cell occurs at its minimum value, the minimum value of R_P can be estimated as follows [31]:

$$R_P = (V_{mp}/(I_{SC} - I_{mp})) - ((V_{OC} - V_{mp})/I_{mp})$$
1.10

The resistor, R_s , can be estimated roughly by calculating the slope of the linear region of the current-voltage curve provided by the manufacturer.

The current of the solar-PV cell depends linearly on the solar irradiance and the cell's temperature according to the following equation [35, 36]:

$$I_{ph} = \left(I_{ph,n} + K_I \Delta_T\right) \frac{G}{G_n}$$
1-11

In the above formula, $I_{ph,n}$ is the generated current (A) at nominal conditions (usually 25° and 1000W/m²), Δ_T is the difference between the actual, T_{op} , and nominal, T_n , temperatures (K). *G* (W/m²) is the solar irradiance on the cell surface, and G_n is the nominal irradiance.

The diode saturation current, I_{sat} , is also dependent on the temperature and may be expressed as follows [37, 38]:

$$I_{sat} = I_{sat,0} \left(\frac{T_n}{T_{op}}\right)^3 exp\left[\frac{qE_g}{ak}\left(\frac{1}{T_n} - \frac{1}{T_{op}}\right)\right]$$
1-12

Where, E_g is the bandgap energy of the semiconductor and $I_{sat,0}$ is the nominal saturation current which is calculated as [31]:

$$I_{sat,n} = \frac{I_{sc,n}}{exp\left(\frac{V_{oc,n}}{aV_{t,n}}\right) - 1}$$
 1-13

with $V_{t,n}$ being the thermal voltage at nominal temperature. Solar panels have a negative temperature coefficient which means that their performance declines as temperature rises. The temperature coefficient dependence of solar-PV panels has been studied by many researchers in order to estimate the annual output of a solar-PV system in an actual operating environment [39, 40]. It is found that an improvement of the temperature coefficient by $0.1\%/C^{\circ}$ results in around 1% increase of the annual output [41]. This highlights the importance of considering the effect of environment on the solar-PV panels' performance. However, many studies that focus on sizing renewable energy systems have ignored this aspect maybe for simplicity reasons [42-45].

1.3.3 Hydrogen energy system (fuel cells, hydrogen storage, electrolyser)

Hydrogen is the most abundant element in the universe in the form of water and hydrocarbons, and exhibits the highest heating value per mass of all chemical fuels. Hydrogen is also regenerative and environmentally friendly. However, hydrogen is not the major fuel for today's energy consumption because is just an energy carrier.
Therefore, in order to use it in energy systems, hydrogen has to be produced, stored and converted to a useful energy form. A hydrogen energy system can provide a sustainable and eco-friendly backup power source for renewable energy systems. This type of energy system usually consists of fuel cells, electrolysers and hydrogen storage. Fuel cells, which convert the chemical energy of hydrogen and oxygen into DC electrical energy [46, 47], may become the power source of the future because they have many advantages over traditional power sources such as diesel generators. Fuel cells generate zero or low pollutant emissions, have higher efficiency and flexible modular structure. The basic structure of a fuel cell (see Figure 1-6) consists of a negatively charged electrode (anode) and a positively charged electrode (cathode) and an electrolyte layer in the middle. In general, there are five major types of fuel cells, differentiated by the electrolyte used in the cells, and they are: proton exchange membrane fuel cell (PEM); alkaline fuel cell (AFC); phosphoric acid fuel cell (PAFC); molten carbonate fuel cell (MCFC); and solid oxide fuel cell (SOFC). Although they are different, they all work in the same general manner. Among the aforementioned types of fuel cells, PEMFC is widely used for stand-alone hybrid renewable energy system applications [48-51]. One of the advantages of the PEMFC is its high power density and high efficiency (40-45%). This makes the technology competitive in transportation and stationary applications. Another benefit is its lower operating temperature (between 60°C and 80°C).



 $\frac{\text{Membrane}}{2\text{H}_2 + \text{O}_2} = 2\text{H}_2\text{O}$

Figure 1-6: Schematic diagram of a PEM fuel cell [30].

An electrolyser breaks down water to produce hydrogen and oxygen. Water electrolysis was firstly discovered by Nicholson and Carlisle at the beginning of the nineteenth century, when they observed the development of hydrogen gas during experiments to replicate the voltaic pile [52]. There are two main categories of water electrolysis: high-temperature water electrolysis; and low temperature water electrolysis [46]. PEM electrolysers and alkaline electrolysers fall into the low-temperature category and are well established and readily available on the market [53]. The PEM electrolyser shares a number of similarities with its PEM fuel cell counterpart. Alkaline electrolysers are a well-proven technology and more favourable than their PEM counterpart because they do not use expensive catalysts, and their unit cost is much lower. Both Alkaline and PEM technologies have the ability to deliver pressurised hydrogen without a compressor, 99.999% pure, dry and carbon-free hydrogen [46]. These features make Alkaline and PEM electrolysers well suited to couple with energy sources such as wind and solar for on-site hydrogen production.

Hydrogen can be stored using six different methods, which are high-pressure gas cylinders; liquid hydrogen in cryogenic tanks; adsorbed hydrogen on materials with a large specific surface area; absorbed on interstitial sites in a host metal at ambient pressure and temperature; chemically bonded in covalent and ionic compounds at ambient pressure; and through the oxidation of reactive metals [54]. Although high-pressure gas cylinders are the most common storage method, the interest in using metal hydrides for hydrogen storage in stationary and small-scale fuel cell applications has increased recently owing to advantageous characteristics such as high volumetric density, large number of charge-discharge cycles and better safety compared to conventional methods [55]. In addition, metal hydride storage canisters store hydrogen at moderate and relatively easy-to-handle pressures between 8 and 30 bar, which is typically the outlet pressure of electrolysers [56]. Therefore, a costly and difficult-to-operate hydrogen compressor can be avoided.

1.3.3.1 Fuel cell modelling

Mathematical models of fuel cells are useful tools to predict their performance. Many models have been proposed in the literature that aim to accurately simulate the performance of different types of fuel cells, ranging from one-dimensional non-isothermal models to three-dimensional non-isothermal and non-isobaric models [57-61]. However, some of the presented models emphasise material structure parameters

which may not be suitable for studying the performance of fuel cells in the context of a complete hybrid energy system. Among the available models, the ones that consider voltage-current characteristics are considered more suitable for long-term performance simulation, because they are not computationally expensive. The reactions that take place at the anode and cathode of a PEM fuel cell are as follows:

Anode:
$$H_2 \to 2H^+ + 2e^-$$
 1.14

Cathode:
$$\frac{1}{2}O_2 + 2H^+ + 2e^- \to H_2O$$
 1.15

The following equation describes the voltage-current characteristics that take into account the activation overvoltage, the ohmic overvoltage from the resistances in the cell as well the mass transport limitations [47, 62]:

$$V_{fc} = V_0 - \alpha_T log(I_{fc}) - ir + m \exp(I_l)$$

$$1.16$$

where, V_0 (*V*) is the open circuit voltage for the PEM fuel cell; α_T (*V*) is the Tafel slope for the PEM fuel cell; I_{fc} (A/m^2) is the current density for the PEM fuel cell; m(V) is a parameter for the overvoltage owing to mass transportation limitations for the PEM fuel cell; and $I_l(m^2/A)$ is the parameter for the overvoltage as a result of mass transportation limitations for the PEM fuel cell. The open circuit voltage of a PEM fuel cell is given as follows:

$$V_0 = V_{rev,fc} + \alpha_T \log(l_0) \tag{1.17}$$

where, $V_{rev,fc}$ (*V*) is the theoretical reversible voltage for the PEM fuel cell and I_0 (A/m^2) is the Tafel parameter for the PEM fuel cell.

1.3.3.2 Electrolyser modelling

The opposite reactions that occur in a fuel cell take place in an electrolyser. The reactions that take place at the anode and the cathode of a PEM electrolyser are as follows [45]:

Anode:
$$H_2 O \to \frac{1}{2}O_2 + 2H^+ + 2e^-$$
 1.18

Cathode:
$$2H^+ + 2e^- \rightarrow H_2$$
 1.19

Through this reaction, water is broken down and hydrogen evolves in the cathode, whereas oxygen evolves in the anode, and at the same time, water is regenerated. In order to model the voltage-current characteristics of the PEM electrolyser, the overvoltage that occurs at the cathode and anode, as well as the ohmic resistance, must be taken into account. The voltage-current characteristics of a PEM electrolyser cell are given as follows [45]:

 $V_{cell} = V_{rev,cell} + ((r_1 + r_2 T)/A)I + K_{elec} \ln(((K_{T1} + K_{T2}/T + K_{T3}/T^2)/A)I + 1)$ 1.20

where, $V_{rev,cell}$ (*V*) is the reversible cell voltage at standard conditions; $r_1(\Omega m^2)$, $r_2(\Omega m^2/^{\circ}C)$ are the parameters of ohmic resistance of each cell; K_{elec} (*V*), K_{T1} (m^2/A), K_{T2} ($m^{2\circ}C/A$), K_{T3} ($m^{2\circ}C^2/A$) are the overvoltage parameters for each cell; *A* is the area of the cell (m^2); and *T* is the cell temperature (°C). The reversible voltage is the maximum voltage that can be applied across the electrolyser's electrodes. The above formula is also applicable for alkaline electrolysers, and the hydrogen production rate for PEM and Alkaline electrolysers can be estimated by Faraday's Law [47].

1.4 HYBRID RENEWABLE ENERGY SYSTEMS

Several methodologies have been used to overcome the drawbacks of renewable energy resources. Utilising more than one renewable energy source to serve the same load is one of the methodologies used to improve reliability. In addition, energy storage devices and/or diesel generators are used to supplement power during the failure of renewable resources [63]. These kinds of multisource power systems and storage facilities are known as 'hybrid renewable energy systems' and there are several viable configurations [64]. Examples include: wind-battery; wind-diesel [65]; photovoltaicbattery [66]; photovoltaic-diesel; wind-battery-diesel [67]; photovoltaic-battery-diesel [68, 69]; and wind-photovoltaic-battery-diesel [70]. Among the aforementioned configurations, only the ones that have no diesel generator can be considered totally renewable. In addition, a wind, solar and hydrogen fuel cell combination may be considered the most suitable for small scale stand-alone applications. Unlike ocean and hydropower energy, which are considered renewable, wind and solar energy are available almost everywhere. Another advantage is that wind and solar energy are totally pollution-free compared to biomass energy, for example, which is also considered renewable but still produce some greenhouse gases, and also needs some pre-processing before being converted to electric power [71]. Hydrogen fuel cells are another power-generation technology that uses chemical reactions, like batteries, to produce electricity. On the other hand, hydrogen fuel cells are similar to diesel generators in the sense that they can generate electricity as long as a fuel (hydrogen and air) is supplied, but with no greenhouse emissions. Moreover, hydrogen fuel cells are less expensive and require less space compared to flywheels and are more reliable alternatives than batteries [72]. Therefore, a stand-alone wind/solar/hydrogen configuration could be a good candidate to provide clean and relatively inexpensive power supply for small remote communities.

1.4.1 Design of hydrogen-based renewable energy systems

Three main interrelated challenges face designers to achieve reliable, efficient and cost-effective hydrogen based renewable energy systems for stand-alone applications. Prolonged profiles, typically of one year, of renewable resources at the project's location are needed to assess the feasibility of using renewable energy technologies for power generation. The issue is that measured wind and solar energy profiles for rural and remote regions are not usually available. Therefore, accurate methodologies to forecast the availability of renewable energy resources in remote and rural regions must be developed. Accurate long-term estimation of the available renewable resources is very important as it helps to avoid over-estimating the energy system. which results in extensive investment in a power system that is not fully used, and underestimating the energy system, which results in designing a power system that is not able to satisfy the load demand. In addition, the short-term prediction of the available renewable energy is also important as it is needed to support wiser power management decisions in hybrid systems. Another challenge is related to considering multiple conflicted objectives when designing hybrid renewable energy systems. Nowadays, objectives such as minimising greenhouse emissions, maximising efficiency and reliability are as important as minimising the cost of energy generation. Unfortunately, these are conflicting objectives and it may not be possible to realise them at the same time. Therefore, design methodologies are needed to design energy systems that possess an optimal compromise between several conflicting objectives. Moreover, a proper coordination between the subcomponents is vital for a hybrid energy system to serve the load, while keeping the operation of each component within an acceptable range of technical constraints. The failure of properly controlling the system may result in degrading the operation and lifetime of the components, as well as not satisfying the load demand. This introduces another challenge for designers to find power management strategies that guarantee optimal system operation.

1.4.1.1 Reliability analysis

The intermittent nature of renewable energy resources such as wind and solar, greatly influences the ability of a hybrid system to generate power continuously. Therefore, power-reliability assessment is an important step in the design of hybrid renewable energy systems. Several reliability analysis methods are used to assess the reliability of hybrid systems such as: Loss of Energy Expected (LOEE); Loss of Load Expected (LOLE); Loss of Load Probability (LOLP); System Performance Level (SPL); and Loss of Load Hours (LOLH) [44, 73, 74]. The most common method is the Loss of Power

Supply Probability (LPSP) index [75], which represents the probability that an insufficient power supply results when the hybrid system is not able to satisfy the load demand over a particular time period [76]. The values of LPSP vary between 0 and 1, with LPSP=1 meaning the load is never satisfied, while LPSP=0 indicates a load will always be satisfied. To apply the LPSP reliability analysis when designing hybrid renewable energy systems, chronological and probabilistic techniques are used. The chronological technique is easy to implement but computationally onerous, and requires the availability of data spanning a certain period of time. In contrast, the probabilistic technique uses probability methods to incorporate the renewables and load intermittency, thus eliminating the need for time-series data.

1.4.1.2 System cost analysis

Several cost analysis models exist, such as the Levelised Cost of Energy (LCOE) [26], Life Cycle Cost (LCC) [77] and Net Present Cost (NPC) [78], and are available in the literature. The LCOE is defined as the ratio of the total annual cost of the system to the annual electricity delivered by the system [79], and has been widely used to evaluate the economics of hybrid renewable energy systems [64]. The NPC is the total present value of a time series of cash flow, which includes the initial cost of all system components, the cost of any component replacements that occur within the project lifetime and the cost of maintenance. The NPC also takes into account any salvage costs of the components at the end of the project lifetime. The system lifetime is usually considered the life of the component that has the longest lifespan. More details about the calculation of NPC can be found in [78, 80].

1.5 **REFERENCES**

- IEA. (January, 2015). Key energy statistics 2014. Available: http://www.iea.org/publications/freepublications/publication/KeyWorld2014.pdf
- [2] Australian Energy Market Operator (AEMO). (2015). Detailed Summary of 2015 Electricity Forecasts: 2015 National Electricity Forecasting Report. Available: file:///C:/Users/Ade/OneDrive/Documents/Thesis/Thesis%20Literature%20revei w/Detailed%20summary%20of%202015%20electricity%20forecasts.pdf
- [3] Geoscience Australia. (2010, 13 March). Austrailan energy resources assessment. Available: <u>http://www.ga.gov.au/scientific-</u> topics/energy/resources/coal-resources
- [4] C. Poinssot, S. Bourg, N. Ouvrier, N. Combernoux, C. Rostaing, M. Vargas-Gonzalez, and J. Bruno, "Assessment of the environmental footprint of nuclear

energy systems. Comparison between closed and open fuel cycles," *Energy,* vol. 69, pp. 199-211, 2014.

- [5] Clean energy council. (January, 2015). Clean ebergy Australia report 2013 Available: file:///C:/Users/Ade/Downloads/Clean-Energy-Australia-Report-2013.pdf
- U. S. Energy Information Administration. (2015). World Crude Oil Prices.
 Available: <u>http://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm</u>
- [7] S. R. Bull, "Renewable energy today and tomorrow," *Proceedings of the IEEE*, vol. 89, pp. 1216-1226, 2001.
- [8] E. Gray, C. Webb, J. Andrews, B. Shabani, P. Tsai, and S. Chan, "Hydrogen storage for off-grid power supply," *International Journal of Hydrogen Energy*, vol. 36, pp. 654-663, 2011.
- H. Siegfried, "Grid integration of wind energy conversion systems," *Publisher: John Wiley & Sons, ISBN X,* vol. 47197143, p. 1998, 1998.
- [10] S. Mathew, "Wind Energy Fundamentals, Resource Analysis and Economics," 2006.
- [11] J. F. Manwell, J. G. McGowan, and A. L. Rogers, *Wind energy explained: theory, design and application*: John Wiley & Sons, 2010.
- [12] Y. Hu, "Optimum design on renewable energy systems by using deterministic and probabilistic approaches," PhD, University of Miami, 2010.
- [13] L. H. Hansen, L. Helle, F. Blaabjerg, E. Ritchie, S. Munk-Nielsen, H. W. Bindner, P. E. Sørensen, and B. Bak-Jensen, *Conceptual survey of generators* and power electronics for wind turbines, 2002.
- [14] J. Matevosyan, "Wind power in areas with limited export capability," 2004.
- [15] A. Westlake, J. Bumby, and E. Spooner, "Damping the power-angle oscillations of a permanent-magnet synchronous generator with particular reference to wind turbine applications," *IEE Proceedings-Electric Power Applications*, vol. 143, pp. 269-280, 1996.
- [16] P. Bauer, S. De Haan, and M. Dubois, "Windenergy and offshore windparks: state of the art and trends," *Proc. of EPE-PEMC, Dubrovnik, Croatia*, p. 15, 2002.
- [17] O. Carlson, J. Hylander, and K. Thorborg, "Survey of variable speed operation of wind turbines," in *Proc. of European Union Wind Energy Conference*, 1996, pp. 406-409.

- [18] D. S. Zinger and E. Muljadi, "Annualized wind energy improvement using variable speeds," *IEEE Transactions on Industry Applications*, vol. 33, pp. 1444-1447, 1997.
- [19] E. Bogalecka and Z. Krzeminski, "Control systems of doubly-fed induction machine supplied by current controlled voltage source inverter," in *Sixth International Conference on Electrical Machines and Drives*, 1993, pp. 168-172.
- [20] Y. Lei, A. Mullane, G. Lightbody, and R. Yacamini, "Modeling of the wind turbine with a doubly fed induction generator for grid integration studies," *IEEE Transactions on Energy Conversion*, vol. 21, pp. 257-264, 2006.
- [21] E. S. Abdin and W. Xu, "Control design and dynamic performance analysis of a wind turbine-induction generator unit," *IEEE Transactions on Energy Conversion*, vol. 15, pp. 91-96, 2000.
- [22] C. Eisenhut, F. Krug, C. Schram, and B. Klockl, "Wind-turbine model for system simulations near cut-in wind speed," *IEEE Transactions on Energy Conversion*, vol. 22, pp. 414-420, 2007.
- [23] M. R. Patel, Wind and solar power systems: design, analysis, and operation: CRC press, 2005.
- [24] T. Van Cutsem and C. Vournas, *Voltage stability of electric power systems* vol.441: Springer Science & Business Media, 1998.
- [25] P. Pillay and R. Krishnan, "Modeling, simulation, and analysis of permanentmagnet motor drives. I. The permanent-magnet synchronous motor drive," *IEEE Transactions on Industry Applications*, vol. 25, pp. 265-273, 1989.
- [26] H. Yang, W. Zhou, L. Lu, and Z. Fang, "Optimal sizing method for stand-alone hybrid solar-wind system with LPSP technology by using genetic algorithm," *Solar Energy*, vol. 82, pp. 354-367, 2008.
- [27] E. Koutroulis, D. Kolokotsa, A. Potirakis, and K. Kalaitzakis, "Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms," *Solar Energy*, vol. 80, pp. 1072-1088, 2006.
- [28] Anhui Hummer Dynamo Co. Ltd. (access date: 2014, December 8). *Hummer*.Available: <u>http://www.china-windturbine.com/product/2000w.html</u>
- [29] B. Ai, H. Yang, H. Shen, and X. Liao, "Computer-aided design of PV/wind hybrid system," *Renewable Energy*, vol. 28, pp. 1491-1512, 2003.
- [30] C. Wang, "Modeling and control of hybrid wind/photovoltaic/fuel cell distributed generation systems," PhD, Montana State University, 2006.

- [31] M. G. Villalva and J. R. Gazoli, "Modeling and circuit-based simulation of photovoltaic arrays," in *Power Electronics Conference* Bonito-Mato Grosso do Sul, Brazil, 2009, pp. 1244-1254.
- [32] S. S. Deshmukh and R. F. Boehm, "Review of modeling details related to renewably powered hydrogen systems," *Renewable and Sustainable Energy Reviews*, vol. 12, pp. 2301-2330, 2008.
- [33] W. Xie and J. Hui, "MPPT for PV system based on a novel fuzzy control strategy," in 2010 International Conference on Digital Manufacturing and Automation (ICDMA) 2010, pp. 960-963.
- [34] M. Taherbaneh and K. Faez, "Maximum power point estimation for photovoltaic systems using neural networks," in *IEEE International Conference on Control and Automation*, 2007, pp. 1614-1619.
- [35] W. De Soto, S. Klein, and W. Beckman, "Improvement and validation of a model for photovoltaic array performance," *Solar energy*, vol. 80, pp. 78-88, 2006.
- [36] Q. Kou, S. Klein, and W. Beckman, "A method for estimating the long-term performance of direct-coupled PV pumping systems," *Solar Energy*, vol. 64, pp. 33-40, 1998.
- [37] K. Hussein, I. Muta, T. Hoshino, and M. Osakada, "Maximum photovoltaic power tracking: an algorithm for rapidly changing atmospheric conditions," *IEE Proceedings-Generation, Transmission and Distribution,* vol. 142, pp. 59-64, 1995.
- [38] R. A. Messenger and J. Ventre, *Photovoltaic systems engineering*: CRC press, 2010.
- [39] M. Kerr and A. Cuevas, "Generalized analysis of the illumination intensity vs. open-circuit voltage of PV modules," *Solar Energy*, vol. 76, pp. 263-7, 2003.
- [40] E. Radziemska and E. Klugmann, "Thermally affected parameters of the current–voltage characteristics of silicon photocell," *Energy Conversion and Management*, vol. 43, pp. 1889-1900, 2002.
- [41] K. Nishioka, T. Hatayama, Y. Uraoka, T. Fuyuki, R. Hagihara, and M. Watanabe, "Field-test analysis of PV system output characteristics focusing on module temperature," *Solar Energy Materials and Solar Cells*, vol. 75, pp. 665-671, 2003.
- [42] D. Nelson, M. Nehrir, and C. Wang, "Unit sizing and cost analysis of standalone hybrid wind/PV/fuel cell power generation systems," *Renewable Energy*, vol. 31, pp. 1641-1656, 2006.

- [43] S. Ashok, "Optimised model for community-based hybrid energy system," *Renewable energy*, vol. 32, pp. 1155-1164, 2007.
- [44] A. Kashefi Kaviani, G. Riahy, and S. Kouhsari, "Optimal design of a reliable hydrogen-based stand-alone wind/PV generating system, considering component outages," *Renewable Energy*, vol. 34, pp. 2380-2390, 2009.
- [45] D. Ipsakis, S. Voutetakis, P. Seferlis, F. Stergiopoulos, and C. Elmasides,
 "Power management strategies for a stand-alone power system using renewable energy sources and hydrogen storage," *International Journal of Hydrogen Energy*, vol. 34, pp. 7081-7095, 2009.
- [46] M. H. Nehrir and C. Wang, *Modeling and control of fuel cells: distributed generation applications* vol. 41: John Wiley & Sons, 2009.
- [47] J. Larminie, A. Dicks, and M. S. McDonald, *Fuel cell systems explained* vol. 2: Wiley New York, 2003.
- [48] W. Wu, V. I. Christiana, S.-A. Chen, and J.-J. Hwang, "Design and technoeconomic optimization of a stand-alone PV (photovoltaic)/FC (fuel cell)/battery hybrid power system connected to a wastewater-to-hydrogen processor," *Energy*, 2015.
- [49] N. Bizon, M. Oproescu, and M. Raceanu, "Efficient Energy Control Strategies for a Standalone Renewable/Fuel Cell Hybrid Power Source," *Energy Conversion and Management*, vol. 90, pp. 93-110, 2015.
- [50] J. P. Torreglosa, P. García, L. M. Fernández, and F. Jurado, "Energy dispatching based on predictive controller of an off-grid wind turbine/photovoltaic/hydrogen/battery hybrid system," *Renewable Energy*, vol. 74, pp. 326-336, 2015.
- [51] D. Rekioua, S. Bensmail, and N. Bettar, "Development of hybrid photovoltaicfuel cell system for stand-alone application," *International Journal of Hydrogen Energy*, vol. 39, pp. 1604-1611, 2014.
- [52] W. Kreuter and H. Hofmann, "Electrolysis: the important energy transformer in a world of sustainable energy," *International Journal of Hydrogen Energy*, vol. 23, pp. 661-666, 1998.
- [53] M. Newborough, "A report on electrolysers, future markets and the prospects for ITM Power Ltd's electrolyser technology," *Retrieved March*, vol. 15, p. 2009, 2004.
- [54] A. Züttel, "Hydrogen storage methods," *Naturwissenschaften*, vol. 91, pp. 157-172, 2004.

- [55] F. Askri, M. B. Salah, A. Jemni, and S. B. Nasrallah, "Optimization of hydrogen storage in metal-hydride tanks," *International Journal of Hydrogen Energy*, vol. 34, pp. 897-905, 2009.
- [56] V. Schroeder and K. Holtappels, "Explosion characteristics of hydrogen-air and hydrogen-oxygen mixtures at elevated pressures," in *International Conference* on hydrogen safety, Congress Palace, Pisa, Italy, 2005.
- [57] A. J. del Real, A. Arce, and C. Bordons, "Development and experimental validation of a PEM fuel cell dynamic model," *Journal of power sources,* vol. 173, pp. 310-324, 2007.
- [58] F. C. Cetinbas, S. G. Advani, and A. K. Prasad, "Three dimensional proton exchange membrane fuel cell cathode model using a modified agglomerate approach based on discrete catalyst particles," *Journal of Power Sources*, vol. 250, pp. 110-119, 2014.
- [59] G. Molaeimanesh and M. Akbari, "A three-dimensional pore-scale model of the cathode electrode in polymer-electrolyte membrane fuel cell by lattice Boltzmann method," *Journal of Power Sources*, vol. 258, pp. 89-97, 2014.
- [60] A. Rowe and X. Li, "Mathematical modeling of proton exchange membrane fuel cells," *Journal of power sources,* vol. 102, pp. 82-96, 2001.
- [61] C. Wang, M. H. Nehrir, and S. R. Shaw, "Dynamic models and model validation for PEM fuel cells using electrical circuits," *IEEE Transactions on Energy Conversion,* vol. 20, pp. 442-451, 2005.
- [62] O. Ulleberg, "Stand-alone power systems for the future: optimal design, operation and control of solar-hydrogen energy systems," PhD, NTNU, Trondheim, Norvège, Norwegian University of Science and Technology, Trondheim, 1998.
- [63] M. H. Nehrir, C. Wang, K. Strunz, H. Aki, R. Ramakumar, J. Bing, Z. Miao, and Z. Salameh, "A review of hybrid renewable/alternative energy systems for electric power generation: configurations, control, and applications," *IEEE Transactions on Sustainable Energy*, vol. 2, pp. 392-403, 2011.
- [64] M. K. Deshmukh and S. S. Deshmukh, "Modeling of hybrid renewable energy systems," *Renewable and Sustainable Energy Reviews*, vol. 12, pp. 235-249, 2008.
- [65] M. Mushtaha and G. Krost, "Sizing a self-sustaining wind-Diesel power supply by particle swarm optimization," in *Computational Intelligence Applications In Smart Grid (CIASG), 2011 IEEE Symposium on*, 2011, pp. 1-7.

- [66] M. Lalwani, D. Kothari, and M. Singh, "Size optimization of stand-alone photovoltaic system under local weather conditions in India," *International Journal of Applied Engineering Research*, vol. 1, pp. 951-961, 2011.
- [67] L. Xu, S. Islam, A. A. Chowdhury, and D. O. Koval, "Reliability evaluation of a wind-diesel-battery hybrid power system," in *Industrial and Commercial Power Systems Technical Conference, 2008. ICPS 2008. IEEE/IAS*, 2008, pp. 1-8.
- [68] S. Shaahid and M. Elhadidy, "Economic analysis of hybrid photovoltaic-dieselbattery power systems for residential loads in hot regions--A step to clean future," *Renewable and Sustainable Energy Reviews*, vol. 12, pp. 488-503, 2008.
- [69] P. Y. Lim, C. V. Nayar, and S. Rajakaruna, "Simulation and components sizing of a stand-alone hybrid power system with variable speed generator," in 9th International Conference on Environment and Electrical Engineering (EEEIC), 2010, pp. 465-468.
- [70] A. Rajoriya and E. Fernandez, "Hybrid energy system size optimization and sensitivity evaluation for sustainable supply in a remote region in India," *International Journal of Sustainable Energy*, vol. 32, pp. 1-15, 2011.
- [71] P. McKendry, "Energy production from biomass (part 2): conversion technologies," *Bioresource technology*, vol. 83, pp. 47-54, 2002.
- [72] M. Rashid, Ed., *Power electronics handbook: devices, circuits, and applications*. Elsevier Inc, 2011, p.^pp. Pages.
- [73] D. Xu, L. Kang, L. Chang, and B. Cao, "Optimal sizing of standalone hybrid wind/PV power systems using genetic algorithms," presented at the Canadian Conference on Electrical and Computer Engineering, Sask, Canada, 2005.
- [74] W. Zhou, C. Lou, Z. Li, L. Lu, and H. Yang, "Current status of research on optimum sizing of stand-alone hybrid solar-wind power generation systems," *Applied Energy*, vol. 87, pp. 380-389, 2010.
- [75] S. Diaf, G. Notton, M. Belhamel, M. Haddadi, and A. Louche, "Design and techno-economical optimization for hybrid PV/wind system under various meteorological conditions," *Applied Energy*, vol. 85, pp. 968-987, 2008.
- [76] H. Yang, L. Lu, and J. Burnett, "Weather data and probability analysis of hybrid photovoltaic–wind power generation systems in Hong Kong," *Renewable Energy*, vol. 28, pp. 1813-1824, 2003.
- [77] L. C. G. Valente and S. C. A. b. de Almeida, "Economic analysis of a diesel/photovoltaic hybrid system for decentralized power generation in northern Brazil," *Energy*, vol. 23, pp. 317-323, 1998.

- [78] R. Dufo-Lopez and J. L. Bernal-Agustín, "Design and control strategies of PV-Diesel systems using genetic algorithms," *Solar energy*, vol. 79, pp. 33-46, 2005.
- [79] H. Yang, L. Lu, and W. Zhou, "A novel optimization sizing model for hybrid solar-wind power generation system," *Solar energy*, vol. 81, pp. 76-84, 2007.
- [80] J. L. Bernal-Agustín, R. Dufo-López, and D. M. Rivas-Ascaso, "Design of isolated hybrid systems minimizing costs and pollutant emissions," *Renewable Energy*, vol. 31, pp. 2227-2244, 2006.

2 CHAPTER 2: OPTIMISATION OF HYBRID RENEWABLE ENERGY SYSTEMS

Optimisation has been applied to several aspects of renewable energy systems including. Optimally designing hybrid energy systems is necessary to utilise the renewable resources efficiently, and obtain the lowest investment with the maximum usage of the system subcomponents. Researchers developed many methods and techniques to optimise the sizing and operation of different configurations of renewable energy systems as well as forecasting the availability of renewable resources. This chapter reviews methods and techniques used to optimise the system sizing and resources forecasting. Identifying research gaps is rendered to the ensuing chapters.

2.1 Component sizing

Various optimisation methods have been used for sizing hybrid renewable energy systems such as graphic construction methods, probabilistic methods, iterative methods and intelligent methods [1-7]. Sizing methods which are based on worse scenarios or average values of solar or wind resources are simple [8, 9], but designs obtained by this methods tend to be oversized because the worst case has a low occurrence probability and the average values are not constant all the time. In this sense, methodologies that use long time series of weather and electrical load profiles are developed, and the most common tool that uses this approach is HOMER software [10-13]. However, as the complexity of the system increases, the number of simulations also increases exponentially, with a consequent increase in the time and effort required. In addition, these methods cannot be helpful if the design involved more than one objective (multi-objective optimisation) and the optimisation time rapidly increases as the design variables grow.

Intelligent optimisation methods have been used extensively for sizing hybrid renewable energy systems, because of their ability to handle complex problems with multi-linear or non-linear cost objectives [14]. These techniques generally mimic the natural biological evolution and/or the social behaviour of species. Such algorithms have been developed to arrive at near-optimum solutions to large-scale optimisation problems, for which traditional mathematical techniques may fail. Various intelligent optimisation techniques for hybrid energy systems sizing are reported in the literature [15-18]. Various intelligent techniques such as Genetic Algorithms (GAs) [19], Particle Swarm Optimisation [6], Fuzzy Logic (FL), Simulated Annealing (SA) [20, 21], Harmony Search (HS) [22, 23], Artificial Bee Swarm (ABS) [24] and Tabu Search (TS) [25] have been utilized by researchers to design hybrid renewable energy systems in a cost effective way. Combinations of the aforementioned techniques have also been used by researches to size hybrid renewable energy systems optimally [22, 26-28]. For more information about the intelligent techniques used for designing and sizing hybrid renewable energy systems, readers are referred to the following two review articles [29, 30]. Among the abovementioned techniques, GAs and PSO has extensively been used for optimising the size of hybrid renewable energy systems. GAs owes more complex structure which makes it relatively harder to code compared to PSO, and the time required to reach an optimal solution significantly increases as the number of optimisation variables increase [30-33]. GAs has the advantage of being able to jump easily out of a local minimum and find the global optimum efficiently [30]. In addition, GAs can be used to code infinite number of parameters which makes them suitable for sizing studies. Although both GA and PSO algorithms have excellent efficiency with similar iterative searching methods, the PSO has some advantages over GA. The computation time of PSO is shorter and requires lower memory capacity which makes it suitable for real-time optimisation applications, where the speed at which the search tool finds an optimal solution is important. However, the reliability for finding the global solution of a search area is lower than GA. In addition, the PSO is less suitable than GA for problems consisting of more than three parameters as PSO is based on a coordinate definition of particles and the mentioned coordinates can only be defined on the x, y, z plane. Therefore, in this research GA will be applied for optimising the component sizing of the proposed stand-alone hydrogen-based renewable energy systems while PSO will be employed for optimising the real-time components coordination. The following subsections briefly describes The GA and PSO techniques. The identification of research shortfalls in the sizing of stand-alone hydrogen-based renewable energy systems is rendered to Chapter 3.

2.1.1 Genetic algorithm

Genetic Algorithm (GA) is an adaptive heuristic search technique based on the evolutionary ideas of natural selection and genetics. As such, it represents an intelligent exploitation of a random search used to solve non-linear optimisation problems. GAs have been applied to solve difficult optimisation problems because of its suitability for problems with non-continuous, non-differentiable and highly non-linear objective functions. The basic GA consists of five components: an initial random population generator; a fitness evaluation unit; genetic operators for selection; crossover; and mutation operations [34]. To solve any optimisation problem, a GA initially generates random solutions and evaluates them according to the defined objective function. The selection operator selects the predefined percentage of initial solutions based on their fitness value [35]. The selected solutions are then utilised by the crossover operator to provide new possible solutions with the aim of achieving higher fitness values. A typical constrained optimisation problem that can be solved using a GA is in the following form:

$$Minimise_{x}[f(x)]$$
 2.1

Subject to the constraint: $x_{min} \le x \le x_{max}$. To solve such a problem using a GA, the variable *x* is formed in an array structure that contains all the problem variables. In addition, a fitness function must be defined as an input to the GA. Moreover, the values for GA operators should be provided before the GA-based optimisation process.

2.1.2 Particle swarm optimisation

PSO is also a population-based stochastic search technique inspired by the social behaviour of flocking birds, schooling fish and swarm theory, and was first presented by Kennedy and Eberhart in 1995 [36]. PSO is similar to other evolutionary optimisation techniques such as GAs. However, unlike GA, PSO is simple in concept and has no evolution operators such as crossover and mutation.

The original PSO maintains a population of particles $(x_1, x_2, ..., x_p)$ which represents possible solutions to the optimisation problem and are initially distributed uniformly around the search space. The position of each particle, x_i , in the swarm is updated as follows [37]:

$$x_{k+1}^i = x_k^i + v_{k+1}^i$$
 2.2

Each particle in PSO is associated with a pseudo-velocity $v_{k+1}^i \left(-v_{max}^i \le v_{k+1}^i \le v_{max}^i\right)$, which represents the rate of the position change for the particle [37]. The new velocity for each particle, v_{k+1}^i , is defined based on its previous velocity, v_k^i , and the distances of its current position, x_k^i , from its own best, as well as the best experienced position of its own informants, p_k^{gi} , according to the following [37]:

$$v_{k+1}^{i} = w_{k}v_{k}^{i} + c_{1}r_{1,k}(p_{k}^{i} - x_{k}^{i}) + c_{2}r_{2,k}(p_{k}^{gi} - x_{k}^{i})$$
2.3

where the subscripts k and i indicate a pseudo-time increment and the number of particles, respectively, r_1 and r_2 represent uniform random numbers between 0 and 1 and are regenerated at each iteration, whereas c_1 and c_2 are cognitive and social parameters, respectively.

2.2 Renewable resources forecasting

Time-series meteorological data are important for the design and feasibility studies of renewable energy systems. The global whether data could be obtained from internet or local meteorological station, but these data are not always available and may not be suitable for deciding the best feasible solutions for energy systems. Satellite data can be used for estimating renewable resources such as solar irradiance. However, these data may not be easily accessible especially in emerging or non-developed nations. Instead, site-to-site basis weather data (typically hourly resolved solar irradiance, wind speed and temperature) are usually needed. Measured records of meteorological variables for extended periods of time are not available for many locations [38]. When measured weather data do not exist, two ways can be mainly used to estimate these data for any location. Firstly, the necessary data may be synthetically generated from monthly-average values of the meteorological data. Secondly, measurements from nearby sites may be extrapolated by making necessary adjustments [39]. While accurate models are needed for the first, the second approach may not be useful in locations with rough earth topology. A lot of research have been done on solar and wind energy resource estimation and analysis [40, 41]. The following subsections review some of methods developed for solar irradiance and wind speed forecasting.

2.2.1 Solar irradiance forecasting

Various computational models are available in the literature including linear regression models [42, 43], satellite-data-based models [44, 45] and NN models [46-49], for solar irradiance forecasting. However, the abovementioned models require the availability of meteorological data or detailed information of atmospheric conditions. As neither developing methodology for forecasting solar irradiance data nor studying the accuracy of existing models are among the objectives of this PhD thesis, a well-known and simple method for estimating solar irradiance is used for solar power estimation purposes. This method was developed by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) algorithm [50], and is widely used by engineering communities, especially for renewable energy applications [51]. This model is simple to implement and can be used to forecast solar irradiance data for any location.

2.2.1.1 ASHRAE model

In the ASHRAE model, the hourly global irradiance (*I*), hourly beam irradiance in the direction of rays (I_N) and the hourly diffusion radiation (I_d) on the horizontal surface of a clear sky are calculated by using the following formulas [52]:

$$I = I_N \cos \theta_Z + I_d \tag{2.4}$$

$$I_N = A \exp[-B/\cos\theta_Z]$$
 2.5

$$I_d = C I_N$$
 2.6

where *A* is the apparent solar irradiance constant, *B* is the atmospheric extinction coefficient and *C* is the diffuse sky factor. The θ_Z shown in equations 2.4 and 2.5 is the zenith angle and its cosine is given as follows:

$$\cos \theta_Z = \sin \phi \, . \sin \delta + \cos \phi \, . \cos \delta . \cos \omega \tag{2.7}$$

In the above equation, \emptyset is the latitude of the location, ω is the hour angle and δ is the solar declination, whose value can be obtained by the following formula [53]:

$$\delta = 23.45 \sin[360 \cdot (284 + n)/365]$$
 2.8

where *n* is the number of days of the year starting from January. The hour angle (ω) is an angular measure of time and is equivalent to 15°h⁻¹. It is measured from noon-based Local Apparent Time (*LAT*).

$$\omega = 15.0(12.0 - LAT)$$
 2.9

The value of the *LAT* can be obtained from the Standard Time (ST) by using the following equation:

$$LAT = ST + ET \mp 4. (STL - l)$$
2.10

In this regard, STL is the standard meridian for the local time zone, l is the longitude of the location and E is the equation of time correction (in minutes).

$$E = 229.2(0.000075 + 0.001868 \cos B - 0.032077 \sin B - 0.014615 \cos 2B - 0.04089 \sin 2B)$$
2.11

where, $B = \frac{(n-1)}{360}/365$ and $n = n^{th}$ day of the year.

2.2.2 Wind resource forecasting

The intermittency of wind energy is one of the biggest challenges to integrating wind power into modern electricity systems. The power generated by a wind turbine depends on the variation of wind speed which affects the reliability and quality of the electricity supply [54]. The ability to accurately predict the availability of wind energy resources is known to be efficient tool to overcome the aforementioned problems and others [55-57]. Several prediction methods are employed to forecast the availability of wind energy, which include persistence, physical, statistical and hybrid methods. In the persistence method, the prediction of wind speed is set equal to the last available measurement. In other words, the last measured value is assumed to persist into the future without any change [58]:

$$\hat{y}(t) = y(t-1)$$
 2.12

where y(t) is the measured value at time step t and $\hat{y}(t+1)$ is the prediction for the next step. The physical methods use meteorological data such as temperature, pressure, surface roughness and obstacles along with wind-speed measurements to forecast future wind speed. In the physical wind speed forecasting methods, complex models are used to perform the predictions which make these methods computationally expensive. However, the accuracy of the physical methods is affected by the variations of wind speed, which limit their usefulness [59]. The statistical methods do not use any predefined mathematical models and rather rely on training with past measurements, using the difference between the predicted and the actual wind measurements in the immediate past to tune model parameters [59, 60]. Numerical Weather Prediction (NWP) model is an examples of statistical prediction methods that are fast and inexpensive to implement. However, NWP usually exhibit systematic errors in the forecast of some meteorological parameters especially near the surface [61]. A methodologies to improve the accuracy of NWP model are proposed in the literature [61]. However, the performance of these models substantially varies between seasons [62]. This highlights the importance of considering the seasonal effect on the accuracy of renewable resources forecasting methods. In addition to Neural Networks (NNs), Auto-Regressive Moving Average (ARMA) models including seasonal-ARMA, Auto Regressive Integrated Moving Average (ARIMA), seasonal-ARIMA and fractional-ARIMA, ARMA with exogenous models are popular time-series based approaches to predict wind speed [63-70]. Generally, NNs outperform ARMA models though this is not necessarily universal, and the NNs prediction accuracy can be further improved by diversifying the training data [63]. Therefore, NNs will be used in this research for wind speed forecasting and the accuracy of this tool will be investigated. Chapter 4 contains further analysis to current studies on the forecasting of wind energy resources. Identifying the research gaps in the forecasting of wind energy resources will also be considered in Chapter 4.

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2.2.2.1 Neural Networks

A Neural Network (NN) is a collection of interconnected computational units (nodes) which mimic the structure of the human brain. Each node has many inputs and a single output that connects it to other nodes. Figure 2-1 shows the basic structure of an NN unit.





The unit output is a function of the summation of the input values multiplied by their corresponding weights. A typical NN consists of several layers of single units, each of which is connected to other units in the ensuing layer. Data are presented to the NN via an input layer, while an output layer holds the response of the network. One or more hidden layers may also exist. To perform any task, the network must first be trained with respect to input-output data-sets until it learns the relationship between the training data. After that, new input data sets may be presented to the network for prediction or classification. The fact that NNs can be trained to recognise the relationships in data from real systems or from physical models, computer programs or other sources, gives them a great advantage over other techniques for modelling complex and non-linear processes without having to assume the form of the relationship between input and output variables.

2.3 Power management strategy

Power management strategy controls how hybrid energy system components work collaboratively to satisfy load requirements. It is also responsible for keeping the system components work within their technical constraints to ensure safe and prolonged operation. Several power management strategies that use reactive algorithms to control the system operation are available in the literature [71-73]. These

strategies use if-else approaches to passively react to the changes of renewable resources and load demand changes. The main conclusion from these studies is that power management strategy strongly affect the components lifetime. There are also studies propose applying optimisation based energy management strategies [74, 75] which operate the system while continuously minimise or maximise a particular cost function using intelligent techniques such as GA [76]. Other strategies use other intelligent techniques such as fuzzy logic [77-79] and NNs [80] for controlling the switching of the system subcomponents. However, many of the proposed "intelligent" power management strategies, especially the ones based on NNs, have not been experimentally validated. Therefore, this research will introduce a methodology for validating NN-based "intelligent" power management strategy. More analysis of the current literature and identifying the research gaps regarding power management strategies for hybrid renewable energy systems are rendered to Chapter 5 and Chapter 6.

2.4 RESEARCH OBJECTIVES

The main focus of this research was on using intelligent techniques to improve the reliability and cost-effectiveness of a hydrogen-based stand-alone renewable energy system. To archive this, research was undertaken focusing on three main aspects involved with the design and operation of stand-alone hydrogen-based renewable energy systems.

The first investigated the effectiveness of using probabilistic (intelligent) search techniques to improve the efficiency of stand-alone hydrogen energy systems, by including design objectives related to the level of renewables penetration alongside cost and environmental footprint objectives. The research did not involve the effect of the system's operation strategy nor compare different types of intelligent search techniques. The second investigated the effectiveness of using prediction (intelligent) techniques for forecasting renewable energy resources in remote areas, where measured profiles are not available and the accuracy of such techniques for forecasting the available renewable power was assessed. The last investigated the effectiveness of using prediction of hydrogen-based renewable energy systems.

The primary objectives of the research project were to develop:

1- A multi-objective sizing methodology for a stand-alone hydrogen energy system that considers the reliability, renewables utilisation, environmental impact, as

well as the system cost using Genetic Algorithms. Such a sizing methodology may help designing more efficient, environmentally friendly and cost-effective hybrid energy system.

- 2- A neural networks training methodology that uses readily available meteorological data at remote location for short-term wind energy and wind power forecasting. Such a methodology may help improve the neural network prediction accuracy and mitigate the effect of seasonal variations of renewable resources on wind power predictions.
- 3- Validate an NN-based (Predictive) power management strategy to control the operation of a stand-alone hydrogen based renewable energy systems. And,
- 4- Investigate the impact of NN-based (predictive) power management strategies on the economic and operational aspects of the system. An intelligent power management strategy based on NNs may help improve renewables utilisation and in turn reduce the hybrid renewable energy systems cost.

Although the conducted research is in the context of Western Australian conditions, the specific objectives of the research project were intended to be generic and applicable to other regions and hybrid energy system configurations.

2.5 RESEARCH SCOPE

Although there are several types of renewable energy resources, the energy resources in this research are confined to wind, and solar energy, when used in conjunction with a hydrogen energy system to supply electric power to remote areas in a stand-alone mode. The main focus is to use intelligent techniques to improve the design and operation of Wind/Solar/Hydrogen systems. The hydrogen energy system used in this research consists of a PEM fuel cell, a PEM electrolyser and near-atmosphericpressure hydrogen canisters. Except for the PEM fuel cell, which has a relatively slow response, the transient characteristics of the sub-components are ignored. In addition, the dynamic characteristics of the power-conditioning units (DC/DC, DC/AC and AC/DC converters), and the dynamics and efficiencies of hydrogen storage, are beyond the scope of this research. Studying the forecasting accuracy of solar irradiance will also not be considered. The optimal sizing and control of the stand-alone power systems studied in this research are investigated on a system operation level.

2.6 RESEARCH SIGNIFICANCE

The research outcomes have significance for the feasibility of stand-alone renewable energy systems to supplying electric power to remote communities, as well as reducing dependence on fossil fuels. The methodologies reported in this research contribute towards improving the design and operation of hydrogen-based stand-alone renewable energy systems that have less environmental footprint, more efficient renewables utilisation and a higher investment return.

2.7 ORGANISATION OF THE THESIS

The ensuing four chapters of the thesis are formed of journal articles, which are either published or under review in peer-reviewed journals followed by a general discussion and conclusions chapters. Brief summaries for these chapters are as follows:

Chapter 3 presents a multi-objective methodology to optimise stand-alone hydrogen systems. The methodology considers three objective functions: minimising net present cost; whole life cycle emissions; and dumped/excess energy. The presented methodology incorporates a novel reliability assessment index that considers start-up transients of back-up power devices.

Chapter 4 investigates factors that can affect the accuracy of short-term wind speed and wind-power predictions when done over long periods, spanning different seasons.

Chapter 5 presents the methodology and experimental validation of a lab-scale (desktop) energy system controlled by an intelligent power management strategy. The tested methodology uses (real-time) neural network predictions to manage the power flow of hydrogen-based stand-alone renewable energy systems.

Chapter 6 investigates the possible impact of intelligent power management strategies of the economic and operational characteristics of stand-alone hydrogen energy systems.

A general discussion for the research methodologies and results followed by general conclusions are presented in **chapter 7** and **chapter 8** respectively.

2.8 REFERENCES

- [1] H. Yang, L. Lu, and J. Burnett, "Weather data and probability analysis of hybrid photovoltaic–wind power generation systems in Hong Kong," *Renewable Energy*, vol. 28, pp. 1813-1824, 2003.
- [2] G. Tina and S. Gagliano, "Probabilistic analysis of weather data for a hybrid solar/wind energy system," *International Journal of Energy Research*, vol. 35, pp. 221-232, 2011.

- [3] G. Tina, S. Gagliano, and S. Raiti, "Hybrid solar/wind power system probabilistic modelling for long-term performance assessment," *Solar Energy*, vol. 80, pp. 578-588, 2006.
- [4] R. Dufo-López, J. L. Bernal-Agustín, and F. Mendoza, "Design and economical analysis of hybrid PV–wind systems connected to the grid for the intermittent production of hydrogen," *Energy Policy*, vol. 37, pp. 3082-3095, 2009.
- [5] D. K. Khatod, V. Pant, and J. Sharma, "Analytical approach for well-being assessment of small autonomous power systems with solar and wind energy sources," *IEEE Transactions on Energy Conversion*, vol. 25, pp. 535-545, 2010.
- [6] M. Sharafi and T. Y. ELMekkawy, "Multi-objective optimal design of hybrid renewable energy systems using PSO-simulation based approach," *Renewable Energy*, vol. 68, pp. 67-79, 2014.
- [7] S. Dehghan, H. Saboori, A. Parizad, and B. Kiani, "Optimal sizing of a hydrogen-based wind/PV plant considering reliability indices," presented at the International Conference on Electric Power and Energy Conversion Systems, Sharjah, United Arab Emirates, 2009.
- [8] A. N. Celik, "Techno-economic analysis of autonomous PV-wind hybrid energy systems using different sizing methods," *Energy Conversion and Management*, vol. 44, pp. 1951-1968, 2003.
- [9] T. R. Morgan, "The performance and optimisation of autonomous renewable energy systems," University of Wales. Cardiff, 1996.
- [10] V. Khare, S. Nema, and P. Baredar, "Optimisation of the hybrid renewable energy system by HOMER, PSO and CPSO for the study area," *International Journal of Sustainable Energy*, pp. 1-18, 2015.
- [11] Homer Energy. (2012). *Homer, (version 2.68 beta)*. Available: http://homerenergy.com/software.html
- [12] M. S. Alam and D. W. Gao, "Modeling and analysis of a wind/PV/fuel cell hybrid power system in HOMER," in *Industrial Electronics and Applications, 2007. ICIEA 2007. 2nd IEEE Conference on*, 2007, pp. 1594-1599.
- [13] N. A. b. A. Razak, M. M. bin Othman, and I. Musirin, "Optimal sizing and operational strategy of hybrid renewable energy system using homer," in *Power Engineering and Optimization Conference (PEOCO), 2010 4th International*, 2010, pp. 495-501.
- [14] K. Bourouni, T. B. M'Barek, and A. Al Taee, "Design and optimization of desalination reverse osmosis plants driven by renewable energies using genetic algorithms," *Renewable Energy*, vol. 36, pp. 936-950, 2011.

- [15] O. Erdinc, B. Vural, and M. Uzunoglu, "A wavelet-fuzzy logic based energy management strategy for a fuel cell/battery/ultra-capacitor hybrid vehicular power system," *Journal of Power sources*, vol. 194, pp. 369-380, 2009.
- [16] K.-S. Jeong, W.-Y. Lee, and C.-S. Kim, "Energy management strategies of a fuel cell/battery hybrid system using fuzzy logics," *Journal of Power Sources*, vol. 145, pp. 319-326, 2005.
- [17] K. Karabacak and N. Cetin, "Artificial neural networks for controlling wind–PV power systems: A review," *Renewable and Sustainable Energy Reviews*, vol. 29, pp. 804-827, 2014.
- [18] M. Safari and M. Sarvi, "Optimal load sharing strategy for a wind/diesel/battery hybrid power system based on imperialist competitive neural network algorithm," *IET Renewable Power Generation*, vol. 8, pp. 937-946, 2014.
- [19] E. Koutroulis, D. Kolokotsa, A. Potirakis, and K. Kalaitzakis, "Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms," *Solar Energy*, vol. 80, pp. 1072-1088, 2006.
- [20] Y. A. Katsigiannis, P. S. Georgilakis, and E. S. Karapidakis, "Hybrid simulated annealing-tabu search method for optimal sizing of autonomous power systems with renewables," *Sustainable Energy, IEEE Transactions on,* vol. 3, pp. 330-338, 2012.
- [21] O. Ekren and B. Y. Ekren, "Size optimization of a PV/wind hybrid energy conversion system with battery storage using simulated annealing," *Applied Energy*, vol. 87, pp. 592-598, 2010.
- [22] A. Askarzadeh, "A discrete chaotic harmony search-based simulated annealing algorithm for optimum design of PV/wind hybrid system," *Solar Energy*, vol. 97, pp. 93-101, 2013.
- [23] A. Askarzadeh, "Developing a discrete harmony search algorithm for size optimization of wind–photovoltaic hybrid energy system," *Solar Energy*, vol. 98, pp. 190-195, 2013.
- [24] A. Maleki and A. Askarzadeh, "Artificial bee swarm optimization for optimum sizing of a stand-alone PV/WT/FC hybrid system considering LPSP concept," *Solar Energy*, vol. 107, pp. 227-235, 2014.
- [25] Y. Katsigiannis and P. Georgilakis, "Optimal sizing of small isolated hybrid power systems using tabu search," *Journal of Optoelectronics and Advanced Materials*, vol. 10, p. 1241, 2008.

- [26] S. Dehghan, B. Kiani, A. Kazemi, and A. Parizad, "Optimal sizing of a hybrid wind/PV plant considering reliability indices," *World Academy of Science, Engineering and Technology*, vol. 56, pp. 527-535, 2009.
- [27] A. Mellit, "Artificial intelligence based-modeling for sizing of a stand-alone photovoltaic power system: Proposition for a new model using neuro-fuzzy system (ANFIS)," in *Intelligent Systems, 2006 3rd International IEEE Conference on,* 2006, pp. 606-611.
- [28] A. Mellit, "ANFIS-based genetic algorithm for predicting the optimal sizing coefficient of photovoltaic supply (PVS) systems," in *Proceedings of the third international conference on thermal engineering: theory and applications*, 2007, pp. 96-102.
- [29] A. Mellit, S. Kalogirou, L. Hontoria, and S. Shaari, "Artificial intelligence techniques for sizing photovoltaic systems: A review," *Renewable and Sustainable Energy Reviews*, vol. 13, pp. 406-419, 2009.
- [30] O. Erdinc and M. Uzunoglu, "Optimum design of hybrid renewable energy systems: overview of different approaches," *Renewable and Sustainable Energy Reviews*, vol. 16, pp. 1412-1425, 2012.
- [31] J. Causa, G. Karer, A. Núnez, D. Sáez, I. Škrjanc, and B. Zupančič, "Hybrid fuzzy predictive control based on genetic algorithms for the temperature control of a batch reactor," *Computers & chemical engineering*, vol. 32, pp. 3254-3263, 2008.
- [32] A. M. Sharaf and A. A. El-Gammal, "A Novel Coordinated Efficient GA-Self Regulating PID Controller for Hybrid PV-FC-Diesel-Battery Renewable Energy Scheme for Household Electricity Utilization," in *Mathematical/Analytical Modelling and Computer Simulation (AMS), 2010 Fourth Asia International Conference on*, 2010, pp. 456-462.
- [33] S. V. Ustun and M. Demirtas, "Optimal tuning of PI coefficients by using fuzzygenetic for V/f controlled induction motor," *Expert Systems with Applications*, vol. 34, pp. 2714-2720, 2008.
- [34] S. M. A. Raza, F. Kamran, and M. Akbar, "Dynamic and scenario based elicitation of genetic algorithms of agents for control of distributed power system networks and renewable energy resources," in *Microelectronics, 2005. ICM* 2005. The 17th International Conference on, 2005, p. 7 pp.
- [35] A. Mellit and S. A. Kalogirou, "Artificial intelligence techniques for photovoltaic applications: A review," *Progress in energy and combustion science*, vol. 34, pp. 574-632, 2008.

- [36] J. Kenndy and R. Eberhart, "Particle swarm optimization," in *Proceedings of IEEE International Conference on Neural Networks*, 1995, pp. 1942-1948.
- [37] M. Clerc, *Particle swarm optimization* vol. 93: John Wiley & Sons, 2010.
- [38] K. Knight, S. Klein, and J. Duffie, "A methodology for the synthesis of hourly weather data," *Solar Energy*, vol. 46, pp. 109-120, 1991.
- [39] M. A. Wahab and K. Essa, "Extrapolation of solar irradiation measurements: case study over Egypt," *Renewable energy,* vol. 14, pp. 229-239, 1998.
- [40] H. G. Beyer and C. Langer, "A method for the identification of configurations of PV/wind hybrid systems for the reliable supply of small loads," *Solar energy*, vol. 57, pp. 381-391, 1996.
- [41] G. Seeling-Hochmuth, "A combined optimisation concet for the design and operation strategy of hybrid-PV energy systems," *Solar energy*, vol. 61, pp. 77-87, 1997.
- [42] J. Ruiz-Arias, H. Alsamamra, J. Tovar-Pescador, and D. Pozo-Vázquez,
 "Proposal of a regressive model for the hourly diffuse solar radiation under all sky conditions," *Energy Conversion and Management*, vol. 51, pp. 881-893, 2010.
- [43] M. Benghanem and A. Joraid, "A multiple correlation between different solar parameters in Medina, Saudi Arabia," *Renewable Energy*, vol. 32, pp. 2424-2435, 2007.
- [44] N. Lu, J. Qin, K. Yang, and J. Sun, "A simple and efficient algorithm to estimate daily global solar radiation from geostationary satellite data," *Energy*, vol. 36, pp. 3179-3188, 2011.
- [45] A. Kemper, E. Lorenz, A. Hammer, and D. Heinemann, "Evaluation of a new model to calculate direct normal irradiance based on satellite images of Meteosat Second Generation," in *Proceedings of the EUROSUN 2008 1st International Conference on Solar Heating, Cooling and Buildings*, 2008.
- [46] A. Mellit, M. Menghanem, and M. Bendekhis, "Artificial neural network model for prediction solar radiation data: application for sizing stand-alone photovoltaic power system," in *Power Engineering Society General Meeting, 2005. IEEE*, 2005, pp. 40-44 Vol. 1.
- [47] M. Benghanem, A. Mellit, and S. Alamri, "ANN-based modelling and estimation of daily global solar radiation data: A case study," *Energy Conversion and Management*, vol. 50, pp. 1644-1655, 2009.

- S. Rehman and M. Mohandes, "Artificial neural network estimation of global solar radiation using air temperature and relative humidity," *Energy Policy*, vol. 36, pp. 571-576, 2008.
- [49] C. Jacovides, F. Tymvios, J. Boland, and M. Tsitouri, "Artificial Neural Network models for estimating daily solar global UV, PAR and broadband radiant fluxes in an eastern Mediterranean site," *Atmospheric Research*, vol. 152, pp. 138-145, 2015.
- [50] A. ASHRAE, "Handbook of fundamentals," *American Society of Heating Refrigerating and Air Conditioning Engineers, Atlanta, GA*, 2005.
- [51] R. Kumar and L. Umanand, "Estimation of global radiation using clearness index model for sizing photovoltaic system," *Renewable energy*, vol. 30, pp. 2221-2233, 2005.
- [52] M. J. Ahmad and G. Tiwari, "Solar radiation models—A review," International Journal of Energy Research, vol. 35, pp. 271-290, 2011.
- [53] J. R. Howell, R. B. Bannerot, and G. C. Vliet, *Solar-thermal energy systems: analysis and design*: Mcgraw-Hill College, 1982.
- [54] B. Parsons, M. Milligan, B. Zavadil, D. Brooks, B. Kirby, K. Dragoon, and J. Caldwell, "Grid impacts of wind power: a summary of recent studies in the United States," *Wind Energy*, vol. 7, pp. 87-108, 2004.
- [55] A. Fabbri, T. G. S. Roman, J. R. Abbad, and V. M. Quezada, "Assessment of the cost associated with wind generation prediction errors in a liberalized electricity market," *IEEE Transactions on Power Systems,* vol. 20, pp. 1440-1446, 2005.
- [56] P. Pinson, C. Chevallier, and G. N. Kariniotakis, "Trading wind generation from short-term probabilistic forecasts of wind power," *IEEE Transactions on Power Systems*, vol. 22, pp. 1148-1156, 2007.
- [57] N. R. Ullah, K. Bhattacharya, and T. Thiringer, "Wind farms as reactive power ancillary service providers—technical and economic issues," *IEEE Transactions* on Energy Conversion, vol. 24, pp. 661-672, 2009.
- [58] T. Burton, D. Sharpe, N. Jenkins, and E. Bossanyi, *Wind energy handbook*: John Wiley & Sons, 2001.
- [59] C. W. Potter and M. Negnevitsky, "Very short-term wind forecasting for Tasmanian power generation," *IEEE Transactions on Power Systems*, vol. 21, pp. 965-972, 2006.

- [60] M. Lange and U. Focken, "New developments in wind energy forecasting," in Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE, 2008, pp. 1-8.
- [61] T. Nielsen, H. Madsen, H. A. Nielsen, P. Pinson, G. Kariniotakis, N. Siebert, I. Marti, M. Lange, U. Focken, and L. V. Bremen, "Short-term wind power forecasting using advanced statistical methods," in *The European Wind Energy Conference, EWEC 2006*, 2006, p. 9 pages.
- [62] P. Pinson, "Estimation of the uncertainty in wind power forecasting," École Nationale Supérieure des Mines de Paris, 2006.
- [63] S. S. Soman, H. Zareipour, O. Malik, and P. Mandal, "A review of wind power and wind speed forecasting methods with different time horizons," presented at the 42nd North American Power Symposium (NAPS), Arlington, USA, 2010.
- [64] Z. Guo, W. Zhao, H. Lu, and J. Wang, "Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model," *Renewable Energy*, vol. 37, pp. 241-249, 2012.
- [65] Q. Cao, B. T. Ewing, and M. A. Thompson, "Forecasting wind speed with recurrent neural networks," *European Journal of Operational Research*, vol. 221, pp. 148-154, 2012.
- [66] H. Liu, H.-q. Tian, D.-f. Pan, and Y.-f. Li, "Forecasting models for wind speed using wavelet, wavelet packet, time series and Artificial Neural Networks," *Applied Energy*, vol. 107, pp. 191-208, 2013.
- [67] G. Sideratos and N. D. Hatziargyriou, "Probabilistic wind power forecasting using radial basis function neural networks," *IEEE Transactions on Power Systems,* vol. 27, pp. 1-9, 2012.
- [68] M. Milligan, M. Schwartz, and Y. Wan, "Statistical wind power forecasting models: Results for US wind farms," *National Renewable Energy Laboratory, Golden, CO*, 2003.
- [69] J. L. Torres, A. Garcia, M. De Blas, and A. De Francisco, "Forecast of hourly average wind speed with ARMA models in Navarre (Spain)," *Solar Energy*, vol. 79, pp. 65-77, 2005.
- [70] P. Pinson, N. Siebert, and G. Kariniotakis, "Forecasting of regional wind generation by a dynamic fuzzy-neural networks based upscaling approach," in *EWEC 2003 (European Wind energy and conference)*, 2003, pp. 5 pages-CD ROM.
- [71] D. Ipsakis, S. Voutetakis, P. Seferlis, F. Stergiopoulos, and C. Elmasides, "Power management strategies for a stand-alone power system using

renewable energy sources and hydrogen storage," *International Journal of Hydrogen Energy*, vol. 34, pp. 7081-7095, 2009.

- [72] D. Ipsakis, S. Voutetakis, P. Seferlis, F. Stergiopoulos, S. Papadopoulou, and C. Elmasides, "The effect of the hysteresis band on power management strategies in a stand-alone power system," *Energy*, vol. 33, pp. 1537-1550, 2008.
- [73] E. Dursun and O. Kilic, "Comparative evaluation of different power management strategies of a stand-alone PV/Wind/PEMFC hybrid power system,"
 International Journal of Electrical Power & Energy Systems, vol. 34, pp. 81-89, 2012.
- [74] P. Rodatz, G. Paganelli, A. Sciarretta, and L. Guzzella, "Optimal power management of an experimental fuel cell/supercapacitor-powered hybrid vehicle," *Control Engineering Practice*, vol. 13, pp. 41-53, 2005.
- [75] L. Xu, J. Li, J. Hua, X. Li, and M. Ouyang, "Optimal vehicle control strategy of a fuel cell/battery hybrid city bus," *international journal of hydrogen energy*, vol. 34, pp. 7323-7333, 2009.
- [76] J. Zeng, M. Li, J. F. Liu, J. Wu, and H. W. Ngan, "Operational optimization of a stand-alone hybrid renewable energy generation system based on an improved genetic algorithm," in *Power and Energy Society General Meeting, 2010 IEEE*, 2010, pp. 1-6.
- [77] P. García, J. P. Torreglosa, L. M. Fernández, and F. Jurado, "Optimal energy management system for stand-alone wind turbine/photovoltaic/hydrogen/battery hybrid system with supervisory control based on fuzzy logic," *International Journal of Hydrogen Energy*, vol. 38, pp. 14146-14158, 2013.
- [78] S. Subiyanto, A. Mohamed, and M. Hannan, "Intelligent maximum power point tracking for PV system using Hopfield neural network optimized fuzzy logic controller," *Energy and Buildings*, vol. 51, pp. 29-38, 2012.
- [79] A. Al Nabulsi and R. Dhaouadi, "Efficiency optimization of a DSP-based standalone PV system using fuzzy logic and dual-MPPT control," *Industrial Informatics, IEEE Transactions on,* vol. 8, pp. 573-584, 2012.
- [80] E. I. Vrettos and S. A. Papathanassiou, "Operating policy and optimal sizing of a high penetration RES-BESS system for small isolated grids," *IEEE Transactions on Energy Conversion*, vol. 26, pp. 744-756, 2011.

3 CHAPTER 3: THE INTERPLAY BETWEEN RENEWABLES PENETRATION, COSTING AND EMISSIONS IN THE SIZING OF STAND-ALONE HYDROGEN SYSTEMS

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This chapter was published as an article in the International Journal of Hydrogen Energy, 2015 vol. 40, Issue 1, pp 125-135. Whilst all efforts were made to retain the original features of this article, minor changes such as the layout, number formats, and font size and style were implemented in order to maintain consistency in the formatting style of the thesis.

3.1 ABSTRACT

Multi-objective Genetic Algorithms are used to optimise three stand-alone hydrogen systems (WG-H₂, WG/PV-H₂ and PV-H₂) under three different objective functions: minimising (hardware) Net Present Cost – NPC (\$), whole Life Cycle Emissions – LCE (CO₂-eq/yr) and dumped/Excess Energy –EE (%) at low demand. Optimisations considering Excess Energy haven't been reported before. Simulations are implemented using MATLAB, incorporate experimentally resolved fuel cell start-up transients, and dynamic profiles for wind speed, solar irradiance as well as electric load demand. Results indicate the significance of integrating fuel cell start-up into the LPSP when optimising systems, another aspect not reported before and a modified LPSP is introduced. Furthermore, when sizing energy systems by reducing LCE, EE, and NPC, the favoured hybrid architecture appears to be WG-H₂ over the others studied. For the same LPSP, an interesting finding is that increased renewables penetration (reduced dumped loads) affects the optimised solution but comes at a cost.

3.2 INTRODUCTION

Because renewable energy resources are unpredictable and intermittent in nature, research has been conducted to better forecast renewables (wind, solar-PV) and their integration into stand-alone [1] and hydrogen systems [2]. Consequently, these technologies are sometimes perceived as having poor reliability compared to traditional decentralised power such as diesel generators [3, 4]. Although there are no greenhouse gases generated by hardware during renewable energy conversion, these devices are still responsible for greenhouse gas emissions during their lifetime (cradle-to-grave) [5-7]. Other problems cited with adopting renewable energy systems relate to

the high cost of conversion technologies and the need to sometimes dump "excess" power generated [8].

Several approaches have been followed to tackle the drawbacks of renewable energy systems. Combining more than one energy source (hybridising) and incorporating means of energy storage are used to increase system reliability [9, 10] and provide limited excess storage. In this regard, batteries, capacitors and hydrogen technology (electrolyser, hydrogen storage and fuel cell) are amongst the most cited (nonthermally based) energy storage means. Lead-acid batteries are traditionally used as short-term energy storage because of low capital cost. However, there are many environmental concerns with using batteries [8] in addition to having relatively small lifespans and appreciable operational and maintenance costs [11]. In contrast, hydrogen storage is perceived as being more eco-friendly and more easily expandable but suffers from relatively high capital cost [12] as hybridisation of storage technologies can increase overall system complexity and, in turn, the cost of the energy system. In addition, a well-founded compromise between the cost of energy storage (battery-vshydrogen) and their associated lifetime environmental impact must be made. This makes it important to choose a combination of components which results in a systematic compromise between design objectives, operational reliabilities and environmental considerations.

Studies have been conducted to optimally size hybrid renewable energy systems with the (sole) objective of minimising system cost. In this regard, Particle Swarm Optimisation (PSO), Tabu Search (TS), Simulated Annealing (SA), Harmony Search (HS) and Artificial Bee Swarm Optimisation (ABSO) have been recently used to minimise energy system cost [13-15]. These good works do not however account for transient device characteristics and only use single objectives. Even so, PSO is found to be the most robust between the aforementioned techniques [14], but its performance subject to the choice of acceleration parameters [16]. Additionally, comparative studies between PSO and Genetic Algorithms (GA's) applied to hydrogen energy systems are not widespread in the literature. The reliability of the system in [13] was evaluated using several indices such as the Loss of Load Expected (LOLE) and Loss of Power Supply Probability (LPSP), both considering only steady state (nominal) power characteristics. A hybrid sizing (Net Present Cost) procedure that combines PSO and Harmony Search has also been proposed by Dehghan et al. [17] to optimally size a hydrogen-based energy system and the resulting reliability evaluated via the Equivalent Loss Factor (ELF) index. Other research [18] has used battery storage and diesel

generators with solar-PV and wind turbines to build small-scale stand-alone hybrid renewable energy systems for remote regions in India, but only considered life cycle cost and environmental impact.

Although cost is an important aspect in the sizing of any energy system, other considerations such as consequential emissions or the reliability of meeting external (electric) loads are also important. To design hybrid energy systems which consider more than one sizing objective (i.e., not just cost, \$/kW-hr), multi-objective optimisation based Genetic Algorithms (GAs) have been used. Examples include sizing a small autonomous renewable energy system with a diesel generator [7] by considering economic and environmental objectives. In such cases, economic objectives are generally to minimise the Cost of Energy (COE, \$/kW-hr) whereas environmental objectives may be to minimise the CO₂ (equivalent) emissions over the project lifetime. In addition to the economic and environmental objectives, Dufo-Lopez and Bernal-Agustin [19] have considered reducing the unmet load as a third objective, thereby including operational (reliability) into their design objectives. However, they only considered steady state characteristics of primary movers (e.g fuel cells) and did not include maximising renewable energy penetration in their optimisation algorithm. The output of multi-objective optimisation algorithms is however not a single solution, but a group of non-dominant solutions where each individual solution cannot be optimised towards one objective without detracting from at least one of the other objectives. This constitutes the third aspect which Dufo-Lopez and Bernal-Agustin and others [7, 19, 20] have not addressed and have left these decisions to system designers to choose. Such optimisation methodologies may not only be considered subjective, but also do not guarantee consistency or that selected solutions are indeed optimal. The approach used in the present paper overcomes these earlier limitations by applying a fuzzy membership function [21, 22] to decide which of the non-dominant solutions represents the optimal compromise between all system design objectives. Moreover, the solutions reached also analyse the effects of integrating experimentally resolved transient startup characteristics of fuel cells.

Additionally, the percentage of waste converted (renewable) energy diverted to dump loads could reach 50% of total power generated [23]. Excess energy conversion may not only indicate oversized devices (e. g fuel cells, solar-PV panels and wind turbines) but also has flow-on effects onto operational, maintenance and decommissioning costs and a systems associated lifetime environmental impact. All these factors affect the techno-economic viability of stand-alone (hybridised) energy systems. This paper also

addresses such shortfalls by investigating the sizing of hydrogen based renewable energy systems in the context of multiple objectives. For a pre-determined reliability of meeting a load, the factors considered are Net Present Cost (NPC, \$), Excess Energy delivered to dump loads (EE, %) and Life Cycle Emissions (LCE, CO₂-eq/yr). The relative impact of the above optimisation is studied using a Multi-objective Genetic Algorithm in the context of three stand-alone hybrid renewable energy system configurations. These configurations also consider two energy storage technologies namely, hydrogen and battery. For the first time, a modified formula for the Loss of Power Supply Probability (LPSP) index, which considers load losses during fuel cell transient start-up, is also introduced to assess its effect on system reliability and its significance if the transient (start-up) characteristics of fuel cells are ignored. This is developed with practical testing to resolve fuel cell (transient) characteristics. In summary, the contributions of the present work focus not only on applying multiobjective optimisation (i.e., the consideration of emissions, cost and renewables penetration) to stand-alone hydrogen systems, but go further. Specifically, the impact of transient fuel cell characteristics on the loss of power supply is seen to be significant in systems which had been sized with these transients neglected. Additionally, a modified LPSP measure is presented and the effects of battery storage, in the context of multi-objective optimisations, are studied for three types of hydrogen systems. The paper is structured as follows: Section 3.3 presents a description of the energy system components. Section 3.4 describes the Power Management Strategies used and Section 3.5 explains the optimisation algorithm. The results are presented and discussed in Section 3.6 followed by the conclusions in Section 3.7.

3.3 SYSTEMS MODEL

A block diagram of hydrogen based hybrid renewable energy system with (and without) battery is shown in Figure 3-1. The key hardware related considerations in the optimisation algorithm are described below.



Figure 3-1: Block diagram of the overall hydrogen based energy systems tested (with and without battery) when interfaced with (i) solar-PV only (PV-H₂), (ii) wind only (WG-H₂) or (iii) wind and solar-PV (WG/PV-H₂).

3.3.1 External Load and Fuel Cell Transient Characteristics

The highly dynamic electric load demand profile, used to guide the sizing process, has a temporal resolution of 15min, covers a one year time span (525,600min) and amounts to a total annual demand of 7,896kW-hr.

The sizing methodology uses LPSP as a reliability index denoting the likelihood of meeting the external (electric) load demand. In stand-alone (not grid connected) systems, LPSP is the ratio of energy deficits (kW-hr) at any time step (t = 15min) at which part of the load demand is unmet relative to the total energy demand (kW-hr) over the year. An LPSP=1 means the annual load was never satisfied while LPSP=0 indicates a load will always be satisfied. The commonly used formulation for LPSP over a given time period T = 525,600min (i.e., a single year) is as follows [24]:

$$LPSP_{common} = \sum_{t=1}^{T} LPS_{FC_nominal}(t) \Delta t / \sum_{t=1}^{T} P_{Load}(t) \Delta t$$
 3.1

In this regard, $LPS_{FC_nominal}(t)$ is the loss of the power supply (unmet load) at the (15min) time interval *t* (not current dependant) and $P_{Load}(t)$ is the load demand (kW-hr) during that time interval. In this study, the value of the LPSP constraint is chosen to be equal to 0.01 ± 0.005 which corresponds to a nominal total unmet load of 79kW-hr (1%) over an annual demand of 7,896kW-hr which corresponds to around 21.63kW-hr per day.

In the system analysed (Figure 3-1), a backup Proton Exchange Membrane (PEM) fuel cell is used to supply the deficit power (total renewables minus requested load) if the renewable power generators (and battery bank) are not sufficient to meet the demand.

The power and hydrogen consumption characteristic curves of a 1.2kW fuel cell (Make: Ballard; Model: Nexa 1.2kW) are used to simulate the performance of the fuel cell [25]. These characteristic curves can be retrieved from the unit's user manual [25]. The LPSP is a key performance indicator to assess the reliability of stand-alone energy systems [8]. However, if only the steady state characteristics of backup power devices (the PEM fuel cell) are assumed to prevail over an entire time step (15min), as is commonly done [13, 26, 27], this formula (Equation 3.1) for calculating the LPSP does not consider the loss of load supply which may arise during the transient start-up of the fuel cell from stand-still. Steady state models assume fuel cells instantly supply the power which is unrealistic. In this research, the transient response of the fuel cell is integrated into the LPSP and experimentally investigated. Figure 3-2 shows a diagram of the experimental setup.



Figure 3-2: Laboratory based set-up to resolve the transient characteristics of the PEM fuel cell.

The transient performance of the PEM fuel cell is studied by measuring the output voltage from the entire stack for step changes in load (currents) between 0-3A and 0-45A. Figure 3-3 shows the load current and the stack voltage measured during the transient operation of the PEM fuel cell. The transient start-up time is the duration for the fuel cell voltage to rise to 98% of the (nominal) steady state voltage. In Figure 3-3, the output voltage and power are observed to take minutes (not seconds) before stabilising. This demonstrates fuel cells cannot respond instantly to load changes and during transient start-ups loads may not be fully satisfied. As a result, an LPSP which relies on only nominal power characteristics will be insensitive to deficits which will actually occur in the field during transient start-up.


Figure 3-3: PEM fuel cell (voltage) response to a step change of load (current). The nominal voltage and current are shown.

The experimentally derived transient times, corresponding to several step current changes, are then used to derive data for the start-up characteristics of the fuel cell (versus load). In turn, this also means start-up time in an energy system will be affected by fluctuating electric loads. This provides a valuable opportunity to investigate the relative impact associated with integrating these transient characteristics into calculating the system's LPSP under a strongly dynamic electric loads.

To account for any loss of power supply over the fuel cell's transients, Equation 3.1 which only considers steady state (nominal) characteristics but is commonly used in the literature [13, 26, 27] to calculate the LPSP, is modified:

$$LPSP_{modified} = LPSP_{common} +$$

$$\left(\sum_{t=1}^{T} LPS_{FC_transient}(t,i) / \sum_{t=1}^{T} P_{Load}(t) \Delta t\right)$$
3.2

The additional term on the right side of Equation 3.2 quantifies loss of power during transient fuel cell start-ups:

$$LPS_{FC \ transient}(t, i_{FC}) = \tau_{FC}(i_{FC}) P_{FC}(t)$$
3.3

In this regard, $P_{FC}(t)$ is the instantaneous fuel cell power at time interval during its transient start-up t, $\tau_{FC}(i_{FC})$ is the fuel cell's transient start-up time at a current i_{FC} . Finally, it is evident from Equation 3.2 that if the transient start-up time of the fuel cell represented by the right hand term is ignored ($LPS_{FC_transient} = 0$), the modified LPSP reverts back to the commonly used (and smaller valued) LPSP as represented by Equation 3.1.

3.3.2 Solar-PV Module

In the simulations undertaken, the characteristics of a commercially available solar-PV module (Make: Heckert Solar; Model: HS-PL 135) consisting of 36 cells are used [28]. The conversion of solar irradiance (kW/m²) into solar-PV power is mathematically modelled [29] and based on a single diode equivalent circuit with the solar-PV cell's current defined by Equation 3.4 [30]:

$$I_{PV} = I_{ph} - I_{sat} \left[exp^{\frac{V_{PV} + R_s I_{PV}}{V_t}} - 1 \right] - (V_{PV} + R_s I_{PV})/R_P$$
 3.4

Here, I_{ph} is the photon current, I_{sat} (8.33A) is the diode reverse saturation current, $V_t = KT_{op}/q$ is the thermal voltage (Boltzmann constant, $K = 1.38 \times 10^{-23}$; Operating temperature, $T_{op} = 48.2^{\circ}$ C; Electron charge, $q = 1.6 \times 10^{-19}$). The value of the series resistance is estimated by calculating the slope of the characteristic curve of the solar-PV module ($R_s = 0.833\Omega$). Regarding the shunt resistance R_P , its value is calculated as follows [30]:

$$R_P = (V_{mp}/(I_{SC} - I_{mp})) - ((V_{OC} - V_{mp})/I_{mp})$$
3.5

where V_{mp} and I_{mp} are the maximum power point voltage (18V) and maximum power point current (7.48A). The nominal open circuit voltage and short circuit current are V_{OC} (22.3V) and I_{SC} (7.95A), respectively. The DC/DC converter shown in Figure 3-1 represents a maximum power point tracker connected to the solar-PV module and is simulated by assuming the module always works at its maximum power point. Model parameters are retrieved from the module datasheet [28] and the output current and voltage of a single cell are I_{PV} and V_{PV} , respectively.

A time-series of solar-PV module power conversion is established over the entire year by feeding a 15min resolved solar irradiance profile into the models. The solar irradiance profile used in this study is predicted using the well-known ASHRAE clear sky model [31] and has been presented by us earlier [1]. This is done because meteorological data for the location corresponding to the Australian wind data site (latitude: -31.75°, longitude: 115.8°) are not available. The incorporation of measured irradiance data can however be easily done if available [2].

3.3.3 Wind Turbine

A commercially available wind turbine (Make: Hummer, Model: 2kW-off grid) is integrated into the energy system simulations. Its power characteristic curve can be retrieved from the literature [1]. To accurately estimate the wind turbine's output power relative to wind data (acquired at 10m), the effect of the turbine hub height (18m) is considered using the following expression:

$$v = v_0 (H/H_0)^{\alpha} \tag{3.6}$$

In this regard, v is the wind speed at the hub height H and v_0 is the wind speed at the reference height H_0 , whilst α is the wind shear exponent coefficient and its value is assumed to be constant over the whole rotor swept area of the turbine ($\alpha = 1/7$ for open land) [32]. This assumption [33] is valid as there are no significant differences between H and H_0 . Otherwise, ignoring the variation of wind speed shear could lead to erroneous estimations of wind energy [34]. The AC/DC converter shown in Figure 3-1 represents a built-in rectifier and its characteristics are included into the turbine's power curve since it represents the relationship between wind speed and net output power. The output power of the wind turbines is estimated using 15min resolved wind speed data, also studied in an earlier work by us [1]. These data are recorded by the Australian Bureau of Meteorology [35].

3.3.4 Electrolyser and Hydrogen Storage

The electrolysers hydrogen production rate is governed by the Faraday's law as follows [36]:

$$\dot{V}_{EL}(t) = \mu_{EL} n_c I_{ele}(t) / C_{H_2}$$
 3.7

In this regard, μ_{EL} is efficiency and taken as 0.7 [36], C_{H_2} is a conversion coefficient (8,604Ahl⁻¹) and I_{ele} is the electrolyser's current at time *t*. The electrolyser (Make: Hydrogen Energy Co., Ltd., Model: QL-2000) operates over various powers within its maximum rated power $P_{EL,max}$ =1kW. For the metal hydride storage in this study, its state of charge is calculated in equivalent energy units per single cylinder (1kg = 141,900 kJ) and by balancing the consumption and production rates of the fuel cell and electrolyser, respectively, according to the following formula [36]:

$$E_{H2}(t) = E_{H2,0} + \int_0^\tau (\dot{V}_{EL} \Delta H / V_T - \dot{V}_{FC}(t) \Delta H / V_T) dt$$
 3.8

Where, $E_{H2,0}$ is the initial ($t_1 = 15$ min) state of charge stored in each hydrogen cylinder (14,190kJ), \dot{V}_{EL} is the electrolyser hydrogen production rate (ls⁻¹), \dot{V}_{FC} is the fuel cell hydrogen consumption rate (ls⁻¹), V_T is a conversion constant (22.4lmol⁻¹), and ΔH is hydrogen's enthalpy (286kJmol⁻¹). The hydrogen storage state of charge at any time interval beyond the first ($t_1 = 15$ min) is therefore [36]:

$$H_{SOC}(t) = (E_{H2}(t)/E_{H2,max}) \times 100$$
(%) 3.9

In this regard, $E_{H2,max}$ is the maximum capacity whereby the limits of charging/discharging are set to $H_{min} = 10\%$ (14,190kJ) and $H_{max} = 100\%$ (141,900kJ), respectively.

3.3.5 Battery

The energy stored in the lead acid battery used in this study is modelled as follows [37]:

$$E_{bat}(t) = E_{bat,0} + \int_0^t V_{bat}(t) I_{bat}(t) dt$$
 3.10

Where $E_{bat,0}$ is the initial battery charge (0.66kW-hr per battery). In addition, $V_{bat}(t)$ and $I_{bat}(t)$ are the battery voltage and current at time *t*. The state of charge of the battery at each time step is defined as follows:

$$B_{SOC}(t) = \left(E_{bat}(t)/E_{bat,max}\right) \times 100 \quad (\%)$$
3.11

In this regard, $E_{bat,max}$ is the maximum battery capacity and the minimum and maximum states of battery charge are $B_{min} = 40\%$ and $B_{max} = 100\%$, respectively.

3.3.6 DC/AC Inverter

An inverter converts DC electrical power to an AC form and is modelled with its efficiency as follows:

$$P_{inv,Load} = P_{in,inv} \mu_{inv}$$
 3.12

Where $P_{inv,Load}$ is the power delivered to the load from the inverter, $P_{in,inv}$ is the inverter's input power and the inverter efficiency is expressed by $\mu_{inv} = 0.95$.

3.4 POWER MANAGEMENT STRATEGY

Power Management Strategies (PMS) control the switching of various energy system devices and therefore impact the overall energy balance. Typically, power produced by solar-PV module(s) and wind turbine(s) is compared with load demand and determines the switching of the fuel cells and energy flows between hydrogen storage. For the PMS used in this research, the simulation time interval is 15min during which the output power of the primary power sources and load demand are assumed to be constant. The two PMS's employed in this study are presented in Figure 3-4. It should be noted, that at each time step (15min), the power generated by the primary sources (wind turbine and solar-PV), P_{Ren} , is calculated and compared to load demand:

$$P_e = P_{Ren}(t) - P_{Load}(t)$$
3.13

Where P_{Ren} is the sum of the power generated by the wind turbines and the solar-PV modules and P_{Load} is the load demand. The comparison result P_e is used to manage

the operation of the fuel cell and affects the system response based on the energy storage media used.



Figure 3-4: Power Management Strategy for a hydrogen based renewable energy system. The battery-less architecture is formed by only the interconnected (shaded) blocks whereas the system with battery is constituted by the entire diagram.

3.4.1 PMS 1: Battery and Hydrogen Storage

If $P_e < 0$ over any 15min time interval, the necessary power to satisfy the load is provided by the lead-acid battery if the battery state-of-charge (B_{SOC}) is higher than the lower limit, B_{min} =40%, and the battery is able to supply the requested power. If the battery state-of-charge is less than B_{min} or the power requested exceeds that in the battery, the required energy is drawn from the hydrogen storage through the fuel cell. If $P_e > 0$, any surplus renewable power is used to charge the battery but when its stateof-charge is at the higher limit (B_{max} =100%), surpluses are directed to electrolysis for hydrogen production. If the electrolyser cannot handle the entire surplus power, $P_e >$ $P_{EL,max}$, or the hydrogen storage is fully charged $H_{SOC} = H_{max}$, the excess power, P_{exc} , is typically dumped in the literature.

3.4.2 PMS 2: Hydrogen Storage (only)

If $P_e < 0$ and the hydrogen storage state-of-charge is higher than the lower limit H_{min} , the power necessary to satisfy the load is drawn from the fuel cell (hydrogen storage). If $P_e > 0$, surplus power is routed to the electrolyser for the hydrogen production but when hydrogen storage is full ($H_{SOC} = H_{max}$) or the electrolyser cannot handle all the surplus power, $P_e > P_{EL,max}$, excess power, P_{exc} , is again directed to the dump load. With both energy storage media above, the amount of excess energy dumped is analysed as part of this study.

3.5 OBJECTIVE FUNCTIONS AND CONSTRAINTS

The sizing methodology employs a multi-objective Genetic Algorithm which iteratively searches for the optimal system configuration (number of each energy system component) that satisfies three objectives. These objectives are minimising the system's NPC, EE and LCE:

$$F = min\{NPC, EE, LCE\}$$
 3.14

3.5.1 Minimisation of NPC

The system Net Present Cost (NPC) is the present value of all energy system components which are incurred over a lifetime, and includes capital, replacement, and operation and maintenance costs, minus the salvage value of components at the end of the projected lifetime.

$$NPC = \sum_{i} NPC_{i}$$
 3.15

To derive the NPC for each type of component within the energy system (NPC_i), Equation 3.16 may be used [13]. In this regard, N_i is the number of units for that type of component, C_{cap} is the capital cost per unit, C_{rep} is the replacement cost per unit, and $C_{o&m}$ is the operation and maintenance cost per unit. Additionally, *ir* is the monetary interest rate (if applicable), and R = 25 years is the projected lifetime of the entire system (in this research taken equal to the lifetime of the solar-PV module). The parameters which help define the salvage worth of the system at its end of lifetime are expressed by *CRF* and K_i which are the Capital Recovery Factor and single payment present worth, respectively:

$$NPC_i = N_i \left(C_{cap} + C_{rep} K_i(ir, L_i, y_i) + C_{o\&m} CRF(ir, R) \right)$$
3.16

$$CRF(ir, R) = ir (1 + ir)^{R} / ((1 + ir)^{R} - 1)$$
 3.17

$$K_i(ir, L_i, y_i) = \sum_{n=1}^{y_i} 1/(1+ir)^{n L_i}$$
3.18

In addition to the above, L_i is the component's lifetime and y_i is number of replacements of the component during the project lifetime $(L_i, L_i \le R)$. The costs, lifetime and size for the components used in the sizing process are presented in Table 3-1 and derived from values in the literature [13, 38-40]. The replacement cost is less than capital cost for some components because not all the (initial) commissioning infrastructure is replaced at the end of the component's lifetime.

Table 3-1: Data for the hardware parameters used in the optimisation: Costs, assumed component lifetimes [13, 38-40], equivalent CO₂ life cycle emissions [7] and the limit on how many multiples of each component can feature in the energy system sized.

Component	Single unit size	Capita I (\$)	Repla- cemen t (\$)	O&M (\$/year)	Lifetim e (year)	LCE (kg CO ₂ - eq/kWh)	N _{i,min}	N _{i,max}
Wind turbine (WG)	2kW	10,200	7,000	140	15	0.011	1	5
Solar-PV module (PV)	135W	310	310	0	25	0.045	1	100
Fuel cell (FC)	1.2kW	10,850	9,300	270	5	0.020	1	10
Electrolyse r (ELC)	1kW	2,000	1,500	100	5	0.011	1	10
H2 storage	1kg	1,300	1,200	15	20	0.011	4	200
Lead-acid battery	55Ah,12 V	120	120	20	5	0.028	1	200
Inverter	1kW	800	750	8	15	0	5	10

3.5.2 Minimisation of Excess Energy (EE)

The excess (dumped) energy is renewable energy that is converted by wind turbines or solar-PV modules but not consumed by the useful load or diverted to storage devices (battery or hydrogen). Although wind and solar resources are "free", conversion to a useful power is costly. Minimising the amount of excess energy can be done by reducing the capacity of the primary generation units and hence increasing renewables penetration. This in turn reduces overall system cost when meeting the same specific

load demand but means the system's ability to meet external load demand becomes more susceptible to uncertainties in wind speed or solar irradiance. The total excess energy produced by the system is the sum of the excess energy at each time step t, and can be expressed as follows:

$$E_{exc} = \sum_{t=1}^{T} P_{exc}(t) \,\Delta t \tag{3.19}$$

In this regard, $P_{exc}(t)$ is the amount of excess power diverted to dump loads over the length of time interval Δt . The percentage of excess energy, from that originally (renewably) derived, is then calculated as:

 $EE = (E_{exc} / \sum_{t=1}^{T} P_{ren}(t) \Delta t) \times 100 \quad (\%)$ 3.20

3.5.3 Minimisation of Life Cycle Emissions (LCE)

The life cycle emissions of the stand-alone renewable energy systems considered are calculated relative to amount of energy converted (or stored) by the system components [7]. Estimating the greenhouse gas emissions (normalised by energy units converted) is preferable because some components are used for most of the year, such as wind turbines and solar-PV, whereas others are used less frequently such as fuel cells and electrolysers [7]. Because the environmental impact of renewable energy technologies in the Australian context is not available, the data of equivalent CO₂ emissions over the lifetime of several system components are retrieved from the wider literature [7] and used in the simulations and listed in Table 3-1. The total life cycle emissions are calculated as the sum of the emissions by the system components over their lifetime and can be expressed as follows:

$$LCE = \sum_{i=1}^{N} \beta_i * E_i \tag{3.21}$$

Where, β_i (kg CO₂-eq/kW-hr) is the equivalent CO₂ emission over the lifetime of a component per kW-hr (Table 3-1) and E_i (KW-hr) is the amount of energy converted (applies to wind turbines, solar-PV modules, electrolysers, and fuel cells with their DC/DC converters) or stored by components (applies to batteries and metal hydrides).

3.5.4 Constraints

The optimisation problem is subject to the following constraints:

$N_{i,min} \le N_i \le N_{i,max}$	3.22

$$H_{SOC,end} \ge H_{SOC,intial}$$
 3.23

Where $N_{i,min}$ and $N_{i,max}$ are minimum and maximum allowable number of units from each component, as hereby the limits used in this research are shown in Table 3-1. The last constraint (comparing the hydrogen storage state of charge at the beginning and end of the year) is set to ensure preserving enough hydrogen inventories at the end of each calendar year.

3.5.5 Selection of the Optimal Solution

The result of solving the optimisation problem described above is not a single solution, but a set of non-dominant solutions called Pareto optimal solutions. For each of these solutions, any of the objective functions cannot be improved without deteriorating at least one of the other objectives (Section 3.5.1-3.5.3). In this study, a fuzzy membership function is used to rank the entire set of solutions and then help select the optimal (compromise). The value of the fuzzy membership function of the *j*th objective function, μ_i , is defined as [22]:

$$\mu_{j} = \begin{cases} 1 & F_{j} \leq F_{j}^{min} \\ (F_{j}^{max} - F_{j})/(F_{j}^{max} - F_{j}^{min}) & F_{j}^{min} < F_{j} < F_{j}^{max} \\ 0 & F_{j} \geq F_{j}^{max} \end{cases}$$
3.24

Where F_j^{min} and F_j^{max} are the minimum and maximum value of the j^{th} objective function. For each non-dominant solution, the normalised membership function μ^k is calculated as:

$$\mu^{k} = \sum_{i=1}^{N_{obj}} \mu_{j}^{k} / \sum_{k=1}^{M} \sum_{j=1}^{N_{obj}} \mu_{j}^{k}$$
3.25

In this regard, *M* is the number of non-dominated solutions and N_{obj} is the number of objective functions. The best compromise solution is the one that has the maximum value of the normalised membership function. The optimisation variables are the numbers of wind turbines, solar-PV modules, fuel cells stacks, electrolysers, hydrogen storage cylinders, batteries and DC/AC inverter capacity. The optimisation algorithm repeatedly updates the values of these optimisation variables and simulates the performance of the proposed energy system. It does so by calling a Simulink model of the system (Figure 3-1) and taking into considerations device switching according to the relevant PMS.

3.5.6 Implementation of the Optimisation Algorithm

The MATLAB optimisation toolbox (v.R2012b) is used to implement the multi-objective Genetic Algorithm. To use the optimisation toolbox, a MATLAB code representing the fitness function, which calculates the values of all objectives (fitness value), has been written as an M-file. To account for the LPSP and the other constraints (Equations 3.22 and 3.23), the algorithm is adopted to eliminate all solutions that do not satisfy those constraints. The constraints related to the bounds on the number of components (Table 3-1) are entered directly into the optimisation toolbox. Because the number of

wind turbines, solar-PV modules or fuel cells, etc., selected by the optimisation algorithm is an integer but the multi-objective Genetic Algorithm under this version of MATLAB does not support solving integer problems, three other M-files representing the creation, mutation and crossover functions that generate integer numbers (to satisfy the problem constraints) have also been considered. The settings used in the multi-objective tool are four subpopulations with 100 individuals (solutions), the crossover probability is 80% and the number of generations is 100.

3.6 RESULTS AND DISCUSSION

The multi-objective sizing methodology described in Section 3.5 is applied to the sizing and optimisation of three types of hydrogen based stand-alone energy systems powering a (remote) residential household. These three configurations are Solar-PV/Hydrogen (PV-H₂), Wind/Hydrogen (WG-H₂) and Wind/Solar-PV/Hydrogen (WG/PV-H₂), with or without battery storage. To show the effect on system reliability (expressed through LPSP) from not considering loads during a fuel cell's transient start-up, LPSP's of the optimal solution based on the common (Equation 3.1) and modified (Equation 3.2) are compared. Results show that for the $PV-H_2$, WG-H₂, and WG/PV-H₂ configurations, the LPSP values derived when neglecting fuel cell transients are 0.005, 0.006 and 0.005, compared to much higher values at 0.018, 0.012 and 0.011 when these transients are included, respectively. The fact that LPSP values more than double if experimentally resolved (device specific) transients are included shows the need to include these when undertaking optimisations. This has largely been overlooked in the literature published to date. It should be noted here that a higher LPSP means less system reliability to meet an external load. Hence, all reported LPSP values beyond this point are based on Equation 3.2.

For each of the hardware configurations considered (Figure 3-1), the optimisation algorithm finds a range of solutions, whereby each solution defines the number of system components (e. g. fuel cells, batteries, etc.) under two different (sizing) methodologies. These plausible solutions are then refined over time (multiple generations) to arrive at the optimal solution under each design methodology. Figure 3-5 shows a sample result demonstrating the improvement in objectives versus generations. The first sizing methodology termed Design Methodology-1, optimises system size whilst considering three objective functions (minimising NPC, EE, and LCE). Alternatively, Design Methodology-2 only considers a single objective function (minimising NPC). The hardware components under each optimal solution are shown in Figure 3-6. Additionally, Figure 3-7 presents the resulting NPC, EE and LCE for each of these hardware configurations, with and without battery.



Figure 3-5: Convergence of the optimisation algorithm.



Figure 3-6: Optimal solutions resulted from both design methodologies for: (a) PV-H₂;
(b) WG-H₂ and (c) WG/PV-H2 systems at LPSP=0.01±0.005. Solutions are for without battery storage (solid) and with battery storage (dashed

From these results, it can be observed that for similar LPSP targets (0.01±0.005), optimal solutions achieved from Design Methodology-1 (min NPC, EE, and LCE) have more hydrogen storage capacity and greater NPC (\$) compared to the Design Methodology-2 (min NPC). This leads to an improved and smaller LCE (kg CO₂-eq/yr) but at the expense of a higher COE (\$/kW-hr). It can also be observed that as the number of battery units increases, it does so at the expense of fewer units related to the hydrogen (fuel cell, electrolyser and hydrogen storage). The reason is because for a given LPSP, the system's NPC (\$) with lead-acid batteries is by far cheaper than integrating fuel cells, electrolyser and hydrogen storage. This however does not

manifest itself when systems are optimised with Design Methodology-1 which considers LCE (kg CO_2 -eq/year) and EE (%) in addition to NPC (\$).

From the sizing results, it is observed that Design Methodology-2 (min NPC) results in solutions with relatively higher excess energy (Figure 3-7b) and greater life cycle emissions (Figure 3-7c) compared to Design Methodology-1 (min NPC, EE, LCE). Furthermore, the excess energy from these solutions (without battery) are at 32% (11,277kW-hr), 45% (13,122kW-hr) and 59% (20,404kW-hr) for PV-H₂, WG-H₂ and WG/PV-H₂, respectively and exceed those with battery. This implies the generation capacity of battery-less systems which are optimised for NPC and designed to meet a specific LPSP, only may be oversized.

Furthermore, the least excess energy is generated by PV-H₂ system (Figure 3-7b) but the life cycle emissions of this system is the highest compared to the other systems when wind is added. This attributed to the much greater LCE associated with solar-PV modules compared to other devices (Table 3-1). In contrast, the highest percentage of excess energy is generated by WG/PV-H₂ system. Among the three systems (with or without battery), WG-H₂ represents the system that results in the optimal compromise between the EE and LCE.

Design Methodology-1 includes minimising the percentage of excess energy (EE) along with economic (NPC) and environmental (LCE) objectives. Hypothetically, one may anticipate that reducing the amount of excess energy would decrease simultaneously the Cost of Energy (COE) because lower dumped power means fewer (smaller) primary movers (wind turbines or solar-PV panels). For the same level of reliability (LPSP), less dumped power also means a greater relative contribution (penetration) from renewable energy in meeting actual load. However, results show that systems whereby lower excess energy is sought (whilst meeting a specific LPSP) are consistently more expensive. To investigate the reason behind this result, the annual cost associated with generating surplus energy which is then dumped as excess is further analysed for one system configuration without battery (WG-H₂). The optimal solution from Design Methodology-1 (min NPC) contains only two wind turbines compared to design Methodology-2 (min NPC, EE, LCE) which has 3 wind turbines (Figure 3-6b).

Due to the high cost of hydrogen pathway components (fuel cells, electrolyser and hydrogen storage), the cost savings gained from reducing the number of primary

movers (wind turbines) is less than the cost of the extra units associated with the hydrogen energy pathway. In this case, the capital cost of the generation units (wind turbines) is reduced by \$10,200, when using Design Methodology-1 while the capital cost of the hydrogen energy pathway (Fuel cell, electrolyser and hydrogen storage) is increased by around \$50,000. This explains why systems designed to meet less dumping of excess energy have a higher COE at 2.29\$/kW-hr (Design Methodology-1) compared to 1.67\$/kW-hr (Design Methodology-2).

Among all systems sized in this study, results show that WG-H₂ with battery provides the optimal compromise between economic, efficiency and environmental objectives. In this instance, the optimised system (WG=2units, FC=1units, ELC=4units, Battery=120units, H2 storage=5units, Inverter=8kW, NPC=\$192,485 and EE=26%) delivers a cost of energy at 1.78 \$/kWh with an associated environmental footprint of 274kg CO2-eq/yr. However, systems that consider increasing renewables penetration for the same reliability (i.e., less power is diverted to dump loads) combined with a small environmental impact (life cycle emissions) have no cost advantage over systems sized using economic objectives only (min NPC). The overall results agree with previous findings which show that stand-alone PV-H₂ systems are not economically competitive compared to WG-H₂ systems [27, 41]. The present research goes further and points out that a PV-H₂ system is also not favourable from an environmental point of view compared to WG-H₂ or WG/PV-H₂. Beccali et al [42] have shown that grid connected large scale WG-H₂ systems have the lowest Cost of Energy (COE) and lowest greenhouse gas emissions.



Figure 3-7: Comparisons between NPC, EE and LCE (a, b and c respectively) for three configurations of hydrogen based energy systems, without battery storage (solid) and with battery (dashed). For all configurations shown, LPSP=0.01±0.005.

Results also show that hydrogen based renewable energy systems can benefit economically from including some battery storage. On the other hand, the present research also indicates the impact of battery storage on the LCE is limited for the hybrid systems studied. Finally, the findings of this study reveal that for the time being, considering minimising the excess energy as an objective during the design of standalone hydrogen based renewable energy systems is not favourable due to the high cost of hydrogen energy devices. This outcome may be worth revisiting in the future if the prices of hydrogen energy devices are reduced [42].

3.7 CONCLUSIONS

Several hybrid renewable energy systems are sized to minimise Net Present Cost (NPC), the Excess Energy (EE) and the Life Cycle Emissions (LCE). Sizing is formulated as a multi-objective optimisation problem and solved using a Genetic Algorithm. Loss of Power Supply Probability (LPSP) is used to measure load meeting reliability in the optimised solutions. In addition, experiments have been conducted to practically resolve the transient start-up time of PEM fuel cell stacks. It is believed such data is used for the first time to modify the LPSP formula in order to provide a more accurate estimate of load meeting reliability. Results show the proposed methodology can help systems designers to more accurately assess the reliability of stand-alone energy systems in meeting a target demand. The techno-economic feasibility and optimisation of renewable energy systems is however very location specific. As such, even though sizing results drawn from this paper are valid only for the location and the load demand profiles employed, more importantly, the sizing methodology used (multiobjective Genetic Algorithms) and techniques derived (modified LPSP) are believed to be more valuable as they are generic and adaptable to other scenarios. The following specific outcomes have been drawn from this research:

- Ignoring the transient response of fuel cell stacks results in hydrogen energy systems which are sized but overestimate their load meeting reliability.
- A modified index to evaluate the load meeting reliability of energy systems is introduced. This accounts for the transient start-up characteristics of fuel cells.
- If the optimisation of a hydrogen system aims to reduce EE and LCE (in addition to NPC), the solutions obtained favour more hydrogen energy pathway equipment at the expense of battery storage.
- Because of the high cost of energy storage devices, a stand-alone energy system with greater renewables penetration (less dumped or excess energy) is more expensive than a system with high excess energy.

- Including limited battery storage, within hydrogen based stand-alone renewable energy systems, reduces the total cost and life cycle (environmental) impact.
- For the considered location and load profile, the WG-H₂ has the best compromise between the objectives tested, compared to PV-H₂ and WG/PV-H₂.

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3.9 REFERENCES

- [1] A. Brka, Y. M. Al-Abdeli, and G. Kothapalli, "Influence of neural network training parameters on short-term wind forecasting," *International Journal of Sustainable Energy*, pp. 1-17, 2014. DOI: 10.1080/14786451.2013.873437.
- [2] D. P. Clarke, Y. M. Al-Abdeli, and G. Kothapalli, "The impact of renewable energy intermittency on the operational characteristics of a stand-alone hydrogen generation system with on-site water production," *International Journal of Hydrogen Energy*, vol. 38, pp. 12253-12265, 2013.
- [3] M. Castañeda, L. Fernández, H. Sánchez, A. Cano, and F. Jurado, "Sizing methods for stand-alone hybrid systems based on renewable energies and hydrogen," in 16th IEEE Mediterranean Electrotechnical Conference, Hammamet, Tunisia, 2012, pp. 832-835.
- [4] A. M. O. Haruni, M. Negnevitsky, M. E. Haque, and A. Gargoom, "A Novel operation and control strategy for a standalone hybrid renewable power system," *IEEE Transactions on Sustainable Energy*, vol. 4, pp. 402-413, 2013.
- [5] W. K. Biswas, B. C. Thompson, and M. N. Islam, "Environmental life cycle feasibility assessment of hydrogen as an automotive fuel in Western Australia," *International Journal of Hydrogen Energy*, vol. 38, pp. 246-254, 2013.
- [6] M. Pehnt, "Dynamic life cycle assessment (LCA) of renewable energy technologies," *Renewable Energy*, vol. 31, pp. 55-71, 2006.
- [7] Y. Katsigiannis, P. Georgilakis, and E. Karapidakis, "Multiobjective genetic algorithm solution to the optimum economic and environmental performance

problem of small autonomous hybrid power systems with renewables," *IET Renewable Power Generation,* vol. 4, pp. 404-419, 2010.

- [8] D. Nelson, M. Nehrir, and C. Wang, "Unit sizing and cost analysis of standalone hybrid wind/PV/fuel cell power generation systems," *Renewable Energy*, vol. 31, pp. 1641-1656, 2006.
- [9] M. Castañeda, A. Cano, F. Jurado, H. Sánchez, and L. M. Fernández, "Sizing optimization, dynamic modeling and energy management strategies of a standalone PV/hydrogen/battery-based hybrid system," *International Journal of Hydrogen Energy*, vol. 38, pp. 3830-3845, 2013.
- [10] B. Escobar, J. Hernández, R. Barbosa, and Y. Verde-Gómez, "Analytical model as a tool for the sizing of a hydrogen production system based on renewable energy: The Mexican Caribbean as a case of study," *International Journal of Hydrogen Energy*, vol. 38, pp. 12562-12569, 2013.
- [11] D. Ipsakis, S. Voutetakis, P. Seferlis, F. Stergiopoulos, and C. Elmasides, "Power management strategies for a stand-alone power system using renewable energy sources and hydrogen storage," *International Journal of Hydrogen Energy*, vol. 34, pp. 7081-7095, 2009.
- [12] D. Ipsakis, S. Voutetakis, P. Seferlis, F. Stergiopoulos, S. Papadopoulou, and
 C. Elmasides, "The effect of the hysteresis band on power management strategies in a stand-alone power system," *Energy*, vol. 33, pp. 1537-1550, 2008.
- [13] A. Kashefi Kaviani, G. Riahy, and S. Kouhsari, "Optimal design of a reliable hydrogen-based stand-alone wind/PV generating system, considering component outages," *Renewable Energy*, vol. 34, pp. 2380-2390, 2009.
- [14] A. Maleki and A. Askarzadeh, "Comparative study of artificial intelligence techniques for sizing of a hydrogen-based stand-alone photovoltaic/wind hybrid system," *International Journal of Hydrogen Energy,* vol. 39, pp. 9973-9984, 2014.
- [15] A. Maleki and A. Askarzadeh, "Artificial bee swarm optimization for optimum sizing of a stand-alone PV/WT/FC hybrid system considering LPSP concept," *Solar Energy*, vol. 107, pp. 227-235, 2014.
- [16] D. P. Clarke, Y. M. Al-Abdeli, and G. Kothapalli, "The impact of using Particle Swarm Optimisation on the operational characteristics of a stand-alone hydrogen system with on-site water production," *International Journal of Hydrogen Energy*, vol. 39, pp. 15307-15319, 2014.

- [17] S. Dehghan, H. Saboori, A. Parizad, and B. Kiani, "Optimal sizing of a hydrogen-based wind/PV plant considering reliability indices," presented at the International Conference on Electric Power and Energy Conversion Systems, Sharjah, United Arab Emirates, 2009.
- [18] A. Rajoriya and E. Fernandez, "Hybrid energy system size optimization and sensitivity evaluation for sustainable supply in a remote region in India," *International Journal of Sustainable Energy*, vol. 32, pp. 27-41, 2013.
- [19] R. Dufo-Lopez and J. L. Bernal-Agustin, "Multi-objective design of PV-winddiesel-hydrogen-battery systems," *Renewable Energy*, vol. 33, pp. 2559-2572, 2008.
- [20] S. F. Fux, M. J. Benz, and L. Guzzella, "Economic and environmental aspects of the component sizing for a stand-alone building energy system: A case study," *Renewable Energy*, vol. 55, pp. 438-447, 2013.
- [21] M. Abido, "A novel multiobjective evolutionary algorithm for environmental/economic power dispatch," *Electric Power Systems Research*, vol. 65, pp. 71-81, 2003.
- [22] T. Niimura and T. Nakashima, "Multiobjective tradeoff analysis of deregulated electricity transactions," *International Journal of Electrical Power and Energy Systems*, vol. 25, pp. 179-185, 2003.
- J. A. Razak, K. Sopian, Y. Ali, M. A. Alghoul, A. Zaharim, and I. Ahmad,
 "Optimization of PV-wind-hydro-diesel hybrid system by minimizing excess capacity," *European Journal of Scientific Research*, vol. 25, pp. 663-671, 2009.
- [24] A. E. S. A. Nafeh, "Optimal economical sizing of a PV-wind hybrid energy system using genetic algorithm," *International Journal of Green Energy*, vol. 8, pp. 25-43, 2011.
- [25] Ballard Power Systems. (access date: 2014, January 10). Nexa power module user's manual man5100078. Available: http://my.fit.edu/~swood/Fuel%20Cell%20Manual.pdf
- [26] C.-H. Li, X.-J. Zhu, G.-Y. Cao, S. Sui, and M.-R. Hu, "Dynamic modeling and sizing optimization of stand-alone photovoltaic power systems using hybrid energy storage technology," *Renewable Energy*, vol. 34, pp. 815-826, 2009.
- [27] Z. Iverson, A. Achuthan, P. Marzocca, and D. Aidun, "Optimal design of hybrid renewable energy systems (HRES) using hydrogen storage technology for data center applications," *Renewable Energy*, vol. 52, pp. 79-87, 2013.

- [28] Solarshop.net. (15. 12. 2013). Technical data heckert HS-PL 135. Available: <u>http://www.solarshop-europe.net/solar-components/solarmodules/heckert_hs-pl-135_m_634.html</u>
- [29] D. Sera, R. Teodorescu, and P. Rodriguez, "PV panel model based on datasheet values," in *IEEE International Symposium on Industrial Electronics*, Vigo, Spain, 2007, pp. 2392-2396.
- [30] M. G. Villalva and J. R. Gazoli, "Modeling and circuit-based simulation of photovoltaic arrays," in *Power Electronics Conference* Bonito-Mato Grosso do Sul, Brazil, 2009, pp. 1244-1254.
- [31] L. Wong and W. Chow, "Solar radiation model," *Applied Energy,* vol. 69, pp. 191-224, 2001.
- [32] B. S. Borowy and Z. M. Salameh, "Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system," *IEEE Transactions on Energy Conversion*, vol. 11, pp. 367-375, 1996.
- [33] D. Bechrakis and P. Sparis, "Simulation of the wind speed at different heights using artificial neural networks," *Wind Engineering,* vol. 24, pp. 127-136, 2000.
- [34] R. Wagner, M. Courtney, J. Gottschall, and P. Lindelöw-Marsden, "Accounting for the speed shear in wind turbine power performance measurement," *Wind Energy*, vol. 14, pp. 993-1004, 2011.
- [35] BOM. (access date: 2011, July 20). *Western Australia weather and warnings*. Available: <u>http://reg.bom.gov.au/wa/</u>
- [36] A. Bilodeau and K. Agbossou, "Control analysis of renewable energy system with hydrogen storage for residential applications," *Journal of Power Sources*, vol. 162, pp. 757-764, 2006.
- [37] S. Pedrazzi, G. Zini, and P. Tartarini, "Complete modeling and software implementation of a virtual solar hydrogen hybrid system," *Energy Conversion and Management*, vol. 51, pp. 122-129, 2010.
- [38] Anhui Hummer Dynamo Co. Ltd. (15. 09. 2012, 19. 09.). *Hummer*. Available: <u>http://www.china-windturbine.com/about.htm</u>
- [39] M. J. Vasallo, J. M. Andújar, C. Garcia, and J. J. Brey, "A methodology for sizing backup fuel-cell/battery hybrid power systems," *IEEE Transactions on Industrial Electronics*, vol. 57, pp. 1964-1975, 2010.
- [40] P. Hearps and D. McConnell. (10. 12. 2013), Renewable energy technology cost review. 1-58. Available: <u>http://www.garnautreview.org.au/update-</u> 2011/commissioned-work/renewable-energy-technology-cost-review.pdf

- [41] H. Caliskan, I. Dincer, and A. Hepbasli, "Exergoeconomic and environmental impact analyses of a renewable energy based hydrogen production system," *International Journal of Hydrogen Energy*, vol. 38, pp. 6104-6111, 2013.
- [42] M. Beccali, S. Brunone, M. Cellura, and V. Franzitta, "Energy, economic and environmental analysis on RET-hydrogen systems in residential buildings," *Renewable energy*, vol. 33, pp. 366-382, 2008.

4 CHAPTER 4: INFLUENCE OF NEURAL NETWORK TRAINING PARAMETERS ON SHORT-TERM WIND FORECASTING

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4.1 ABSTRACT

This paper investigates factors which can affect the accuracy of short-term wind speed prediction when done over long periods spanning different seasons. Two types of Neural Networks are used to forecast power generated via specific horizontal axis wind turbines. Meteorological data used is for a specific Western Australian location.

Results reveal that seasonal variations affect the prediction accuracy of the wind resource, but the magnitude of this influence strongly depends on the details of the Neural Network deployed. Factors investigated include the span of the time series needed to initially train the networks, the temporal resolution of this data, the length of training pattern within the overall span which are used to implement the predictions and whether the inclusion of solar irradiance data can appreciably affect wind speed prediction accuracy. There appears to be a relatively complex relationship between these factors and the accuracy of wind speed prediction via Neural Networks. Predicting wind speed based on Neural Networks trained using wind speed and solar irradiance data also increases the prediction accuracy of wind power generated, as can the type of network selected.

4.2 INTRODUCTION

Wind represents a clean and sustainable energy source which makes it a promising alternative to fossil fuels. On average, global wind power generation capacity has increased by 25% over the last years to reach 238 Gigawatts (GW), but is expected to grow by another 255 GW by 2016 [1]. Combining wind with other renewable energy resources, such as solar energy and an energy storage means like hydrogen, can help build a 100 precent renewable energy system for small applications [2, 3]. However, increasing wind power penetration requires a number of major challenges to be addressed, including the use of realistic models to determine techno-economic

feasibility as well as utilising accurate wind speed predictions to better assess overall viability and the impacts on ancillary service requirements [4]. As with other renewable sources such as solar irradiance, the intermittent and seasonal nature of wind speed is a major hurdle against the utilisation of wind energy systems. For these reasons, wind speed prediction can play an important role in determining the overall feasibility of a renewable energy system and the scale of energy storage media such as batteries or hydrogen [5-8]. In this regard, wind power forecasts can be classified based on the prediction timescale into four categories, namely: very short-term (few seconds to 30 minutes ahead); short-term (30 minutes to 6 hours ahead); medium-term (from 6 hours to one day ahead); and long-term (one day to one week ahead) [5].

Among several methods, Neural Networks (NN) are excellent for predicting variables which are nonlinear or stochastic in nature and have therefore been used to forecast wind speed. The advantage of Neural Networks is that there is no need to base the predictions on preconceived mathematical models. Instead, the methodology relies on samples of training data (historical records of wind speed) to predict patterns of future wind power availability using an "intelligent" self-iterating numerical process which is presented as data intensive. The literature cites numerous investigations into the use of Neural Networks for wind speed prediction [9-16] but the majority of the work done to date uses historical wind speed data as the only (meteorological) parameter to train the networks. Very few exceptions exist to this with some adding other parameters such as ambient temperature and humidity when predicting wind speed [17].

When basing predictions (largely) on wind speed data, several attempts have been made to perform very short-term wind energy forecasting using "intelligent" techniques such as Neural Networks [13, 18-20]. Ricalde et al. used Neural Networks for wind speed forecasting and compared between different networks [18]. However, limited wind speed data covering five hours (only) was used to train and test the networks which raise questions on the sensitivity of this methodology in predicting wind speed over longer periods of time. The current study will show that deploying networks over longer periods (like one year) is paramount in order to capture seasonal variations which have an impact on the accuracy and will address this shortfall by applying short-term predictions (1 hour ahead) over an extended period spanning multiple seasons. Welch, Ruffing and Venayagamoorthy similarly trained three types of Neural Networks to predict (fifteen minutes ahead) wind speed using wind speed, temperature and humidity as training data [21]. Their results showed that although some Neural Networks outperform others, this improved accuracy comes at the expense of longer

training time. Similarly, the use of training data spanning only one week may not allow an analysis against long-term (seasonal) effects. Reikard also used Neural Networks for short-term wind speed forecasting with both wind speed and temperature used for training [10]. The use of additional meteorological data (i. e. temperature) in the training was found to reduce the forecast error for wind speed but the methodology applied also showed that Neural Network prediction accuracy decreases as the temporal prediction range grows (for longer periods ahead). The current paper will show that seasonal effects should be factored in with long-term predictions but the prediction accuracy is strongly affected by the length of (historical) data used for training the Neural Network (varied between 5 hours and 168 hours). Alternatively, long-term wind power forecasting has been conducted by Cali at al. [17] using a multi-model approach with wind speed, wind direction, ambient pressure, temperature and humidity as training data. However, the predictions were implemented for relatively large time-steps which render the wind power predictions at a much longer temporal resolution than typically expected variations in load (demand) that wind energy systems need to meet. As such, investigating seasonal parameters which have the propensity to affect short-term forecasts when applied over prolonged periods, spanning many seasons, is important.

In addition to research undertaken into the effect of meteorological parameters on the accuracy of Neural Network predicted wind speed, the effects of temporal resolution for time steps and the size of data used to train a Neural Network has also been done and the results showed that only one year training data can provide satisfactory prediction accuracy of monthly wind energy [22] . However, prediction of long-term (monthly) wind energy was only investigated. Additionally, other studies have applied Neural Networks to wind power predictions of up to 30 hours ahead [23], but the effect of including other meteorological parameters such as solar irradiance, to help refine wind power predictions, was not done. More importantly, the impact of changing the Lengths of Training Pattern (LTP) on the prediction accuracy was also not investigated. A combination of Neural Network and Genetic Algorithm (GA) has also been used for short-term wind power predictions [24] where it has been found that combining GA with Neural Networks improves the prediction accuracy. However, results also showed that prediction accuracy is affected during periods of strong variation in wind speed. This suggests that more investigation into the effect of seasonal variations on the accuracy of Neural Network predictors may also be warranted whereby parameters, such as temporal resolution of training data, are investigated if they have an effect on the

accuracy of wind speed prediction. In this regard, the current research also investigates this issue with different time steps of wind speed data (0.5 hour to 3 hours).

With the above in mind, there have been no studies which the present authors are aware of that investigate the effect of seasonal variations onto the prediction accuracy of wind speed using Neural Networks. Moreover, the current research also investigates the significance of simultaneously including location-specific solar irradiance data (W/m²) on the accuracy of wind power predictions. This work is done across seasons and also investigates the effect of the LTP and temporal resolution on the accuracy of short-term wind energy predictions. Measured wind speed data for a Western Australian location are used to implement the predictions and the power characteristics of two wind turbines (2kW, 30kW). The paper is divided as follows: Section 4.3 describes the methodology including the wind data, wind turbines, solar irradiance data and Neural Networks used; Section 4.4 presents the results followed by the discussion in Section 4.5 and finally the conclusions in Section 4.6.

4.3 METHODOLOGY

Wind speed is stochastic in nature, but once predicted, the available wind energy can be estimated to reasonable accuracy using a suitable wind turbine model. In this paper, short-term wind energy forecasting is performed using two types of Neural Networks, namely: Feed Forward (FF) and Radial Basis Function (RBF) Neural Networks. These two techniques are categorised as supervised networks because the training algorithm is initially developed using known pairs of input-output patterns (i.e, a historical time series of calendar date versus wind speed, wind speed and direction, or wind speed and solar irradiance). The forecasting process is tested over a prolonged period (one year) so as to identify the effect of seasons on prediction accuracy. Although the forecasting is done over one year period, the prediction step where mainly an hourahead, i.e., 8760 predictions are done to forecast the wind speed over one year.

4.3.1 Wind data and wind turbine models

The available time series consists of half hourly resolved wind speed and direction data measured by the Bureau of Meteorology (BOM) at a height of 10 meters at the Ocean Reef meteorological station (Western Australia, latitude: -31.75°, longitude: 115.8°) [25]. These data cover a period from January 2001 to December 2009. Data spanning either a single year (2001) or six years (2001-2006, around 70% of the available data) are used to first formulate and train the Neural Networks while data for the years 2007-2009 is subsequently used for testing accuracy. In this study, the temporal resolution of

the (source) training data is half hour based. However, to help study the effects of using other resolutions such as hourly, two hours and three hours are also investigated by binning the half hourly data and deriving average wind speeds over the binned periods. Lower resolutions such as weekly or monthly are not considered because these time steps will unnecessarily smooth much of the intermittency characteristics of wind speed as well as impact the ability of the Neural Networks to resolve seasonal effects. To convert the kinetic energy of wind speed to wind power, the power characteristic curves of commercially available wind turbines are used. In this research, the characteristics of 2kW and 30kW off-grid wind turbines are considered and Figure 4-1 gives the power-vs-wind speed curves for both turbines with basic operating data being available [26].



Figure 4-1: Power curve of off-grid wind turbines [26]. Power generated has been normalised by the respective (peak) power capacity.

The hub height of a wind turbine affects the generated wind power [27]. To accurately estimate the power extracted by the wind turbine, the effect of wind shear, which represents the variation of wind speed with elevation, is typically considered. In most studies, the wind speed shear is described by the shear exponent coefficient (α) shown in equation (4.1). Because the modelled wind turbines operate at a height of 18m, but the meteorological wind data is originally measured at 10m, each data point for wind speed is revised to the operating height of the wind turbine [28]:

$$v = v_0 (H/H_0)^{\alpha} \tag{4.1}$$

In this regard, v and v_0 are the wind speed at H and H_0 , respectively, whilst α is the wind shear exponent coefficient. The value of this coefficient has been taken equal to 1/7 commensurate with the value for open land because the location for which the wind power modelling is being undertaken is an unobstructed costal land spot [28]. It is worth noting that whilst the value of the shear exponent coefficient for a particular area

is not constant along the whole rotor swept area of the wind turbine, ignoring the effect of the wind shear coefficient is proven to result in overestimating the wind power extracted from a wind profile for large turbines. This is particularly evident for the cases where the hub height is much greater than the height of the meteorological anemometer used to measure wind speed [29, 30]. Previous studies have also shown variations of wind shear coefficient is insignificantly changed across seasons (summer and autumn compared to winter and spring) [31]. Therefore, in this study a single wind shear coefficient is considered across all seasons.

4.3.2 Solar irradiance data

In order to train the Neural Networks on both wind speed and solar irradiance at the relevant geographical location, solar irradiance data has been derived using the ASHRAE clear-sky model [32]. The parameters of the ASHRAE model are retrieved from the literature [33]. Before the ASHRAE derived (hourly) solar irradiance data was used in the Neural Networks, its accuracy was checked against daily total measured solar irradiance data [34]. This process can be undertaken when no well resolved (e. g. hourly) exists. Figure 4-2 shows these comparisons whereby the data derived using the ASHRAE model (for each day) has been formed by summing the hourly resolved predictions over 24 hours. The figure shows the irradiance predictions based on the clear sky model are able to accurately follow the peak solar irradiance values. It should be noted here that any other reasonably accurate model (or even measured data) could have also been used to demonstrate the validity and effects of coupling wind speed predictions with representative solar irradiance data.



Figure 4-2: A comparison of daily (cumulative) total solar irradiance derived using the ASHRAE model compared to measured (meteorological) daily totals data. (latitude: - 31.75⁰, longitude: 115.8⁰, 2004).

4.3.3 Neural Networks

Neural Networks consist of interconnected computational units which imitate the structure of biological neurons. These neurons are independent processing units and the connections between these units (weights) are used to store the acquired data. In this paper, FF-NN and RBF-NN are used to forecast wind speed (only) using different combinations of meteorological training data. The general structure of these networks, shown in Figure 4-3, comprises of an input layer, a hidden layer, and a linear output layer. The function of the input layer is to distribute input data in order to initiate the computations. Typically, the span of the time series used to train a Neural Network, for example a single year which can be hourly resolved to yield 8760 data points, is further subdivided into batches. The number of data points in each batch dictates the number of neurons in the input layer. For example, an LTP of 10 hours when half hourly resolved wind speed data is used will result in 20 neurons in the input layer, for both FF-NN and RBF-NN. The output of any neuron in the hidden layer of a FF-NN is a result of activating a sigmoid function using the weighted sum of the input signals. The sigmoid activation function has the following form [35]:

$$f(z) = 1/(1 + exp(-\alpha z))$$
 4.2

In this regard, \propto is the slope parameter of the sigmoid function and z is the weighted sum of neuron inputs which is given as:

$$z_k = \sum_{j=1}^M w_{kj} y_j \tag{4.3}$$

In the above equation, y_j is the input signal, w_{kj} is the connection weight and M is the number of values in the input pattern. The connection weights are dictated by the learning algorithm which the Neural Network uses when being training on historical data. In this study, three different algorithms were trialled (the gradient decent algorithm, Levenberg-Marquardt algorithm and adaptive gradient decent algorithm). Based on preliminary testing, it was observed the adaptive gradient decent algorithm yielded the best accuracies and, as such, was deployed in the FF-NN throughout the results which appear in this paper. The output of the sigmoid function is only positive numbers between 0 and 1. Each neuron in the Neural Network compares the output of its activation function against a predefined threshold to decide whether to produce an output or not. In this research, the number of hidden neurons in the FF-NN was taken to be 10 in agreement with the literature [30, 36]. The design of a Feed Forward Neutral network also usually involves the selection of many control parameters. As there is no commonly agreed upon consensus (in the published literature) in relation to the specific rules for nominating these parameters, an iterative process was

undertaken to resolve the best set of these which satisfy a pre-set convergence criteria (the performance goal). Table 4-1 lists the value of these control parameters.

The difference between FF-NN and RBF-NN lies mainly in activation function as well as the role and number of neurons in the hidden layer. The activation function of FF-NN is a sigmoid function whereas for the RBF-NN its activation function for the hidden neurons is a Gaussian function and expressed as [6]:

$$f(y_p - c_i) = exp\left(-(1/2\delta_j^2) \|y_p - c_i\|^2\right)$$
4.4

In this regard, *c* and δ are the centre and the mean square deviation of the Gaussian function and y_p is the p^{th} input pattern whereby the Gaussian function is bell-shaped with a maximum of 1. Neurons are activated (produce an output) based on how close the net input is from a chosen value of averaged inputs. While FF-NN acts as a global approximation network, since the network's output is decided by all neurons of the hidden layer, RBF-NN acts as local approximation network. This means the hidden layer in RBF-NN redistributes the input data and each output is determined by specified hidden units [37]. Further details on the training algorithm of RBF-NN are also available in the literature [6, 37].



Figure 4-3: General structure of FF-NN and RBF-NN: (a) training phase (2001-2006); (b) test phase (2007-2009).

The other difference between a FF-NN and RBF-NN is the former uses a fixed number of neurons in the hidden layer whereas the latter uses a variable number of neurons in the hidden layer (self-defined by the Neural Network). Training coefficients of Radial Basis Function Neural Network are also listed in Table 4-1. The consequences of the above are that RBF-NN trains itself over different ranges of the training data (e. g. different ranges of wind speed) where FF-NN is trained on the total range.

Network type	Value	
	Momentum constant	0.6
	Learning rate	0.8
FF-NN	Performance goal	1e-4
	Number of hidden neurons	10
	Spread of radial basis function	20
RBF-NN	Performance goal	1e-5

 Table 4-1: Training coefficients of the Neural Networks used.

4.3.4 Accuracy

The accuracy of hourly wind speed and wind power predictions is expressed as the Absolute Percentage Error (APE) which is calculated as follows:

$$APE = |(y(t) - \hat{y}(t))/y(t)| \times 100\%$$

4.5

The Mean Absolute Percentage Error (MAPE) is used to assess the overall accuracy of the used Neural Networks and it is calculated as follows:

$$MAPE = (1/N) \sum_{i=1}^{N} APE$$

4.6

In the above equations, y(t) is the measured wind speed over a time interval (t), $\hat{y}(t)$ is the predicted wind speed (over the same time interval) and *N* is the number of data points in each year. The time interval (t) represents the resolution of the training and test data (0.5, 1, 2 or 3hours). In the plots and tables which follow, the overall prediction accuracy is expressed by calculating the median value of *APE*, *s* and the median value of *MAPE*, *s* for the test data (2007, 2008, and 2009).

4.4 RESULTS

In this research, the effect of four training parameters on the prediction accuracy of FF-NN and RBF-NN when applied to wind energy prediction is investigated, namely the span of training data, the resolution of training data, the Length of Training Pattern (LTP) and the type of training data.

4.4.1 Span of training data

To demonstrate the effect of the span of training data on the prediction accuracy of FF-NN and RBF-NN, Both Neural Networks are trained using hourly resolved data which spans either a single year (2001) or six years (2001-2006) with the LTP fixed at 10 hours. The prediction error corresponding to each set is shown in Figure 4-4. Whilst the length of training history does not appear to affect the errors qualitatively, the

results do reveal that using six years data set to train the FF-NN provides a marginal improvement in the prediction accuracy, compared to one year training data sets. Quantitatively, no appreciable improvement occurs with RBF-NN, which the results also show already has an accuracy of about one order of magnitude better than FF-NN. This also indicates that RBF-NN may be more accurate than FF-NN for the same span (size) of data set.



Figure 4-4: The effect of the span of training data on the prediction accuracy. Wind speed training data (only) are used: (a) FF-NN; (b) RBF-NN.

4.4.2 Resolution of training data

The effect of temporal resolution of the historical training data is also investigated whereby hourly, two hours and three hours' time series are formed by averaging the original (measured) half hourly meteorological data. Figure 4-5 shows a comparison between the prediction accuracy related to using different temporal resolutions over a single season. A single season is used in this analysis (Figure 4-5) because, as will become evident from this study, strong seasonal effects can manifest themselves. The results show that prediction error for Neural Networks appears best for hourly resolution compared to the others. One distinctive feature from these results is that

using half hourly resolution appears to provide the least accuracy compared to 1-3 hours resolution. This may be due to the fact that half hourly wind speed data more realistically represents the variability of wind speed which results in a greater degree of uncertainty when the Neural Networks attempt to resolve the wind speed over the next time period. More comment and data analysis in relation to this is given within the Discussion section. With the above in mind, the ensuing results were all derived for Neural Networks trained using (hourly resolved) six years training data set.



Figure 4-5: The effect of different training data resolutions of the prediction accuracy of Neural Networks: Wind speed training data (only) are used: (a) FF-NN; (b) RBF-NN.

4.4.3 Type of training data and LTP

To further study the effect of the LTP on the prediction accuracy of the employed Neural Networks, both FF-NN and RBF-NN are trained with four different Lengths of Training Patterns (5, 10, 60 and 168 hours). This is an important consideration because even if the networks are trained using hourly resolved historical data, the LTP dictates how far back in the time-series should the network consider when predicting each next (hourly) time step. A shorter LTP may be hypothesised to yield better predictions if applied to a stochastic parameter such as wind speed. An additional hypothesis to test is, in addition to LTP, what impact on the accuracy of predicted wind speed is associated with using different combinations of (historical) meteorological data. To resolve this question, the training data is also made up of three different combinations of meteorological data: wind speed (only), wind speed and direction, or wind speed and solar irradiance. Figure 4-6 presents the overall trends for the prediction error in both FF-NN and RBF-NN when predicting hourly resolved wind speed averaged over three years ahead (2007-2009). In the results shown, the Neural Network is trained using wind speed data (alone) and the different seasons are also denoted according to the Australian Bureau of Meteorology (BOM) [25]. In this regard, the national summer season is made up of the three (hottest) months of December, January and February. These results show that for both FF-NN and RBF-NN, the accuracy is not consistent throughout the year but experiences a relative trough (low range) during autumn and winter. Outside this period, errors increase and reach their highest values during summer and spring. These results clearly indicate that prediction accuracy for wind speed varies across the year. Moreover, when wind speed data (only) is used to train the Neural Network, the accuracy of both networks tested in this study remains prone to seasonal influences, even though in this instance RBF-NN is clearly more accurate than FF-NN. These results also demonstrate that more research is needed into the veracity of different prediction methodologies which are undertaken over only relatively short periods (e.g., over a week or few months only) as these may fail to resolve longer seasonal trends. This also exemplifies the need for the accuracy of wind speed prediction methods to be tested over prolonged periods (e.g. one year or more) so as to capture such seasonal influences. Unfortunately, it would appear that research into predicting wind speed (and power) over prolonged periods (to account for seasonal influences) is not always apparent in the published literature.



Figure 4-6: Prediction errors using 168 hour input data of wind speed (only) for the years 2007-2009: (a) FF-NN; (b) RBF-NN. The first day in the figure corresponds to 1st January.

Figure 4-7 shows the effect of changing LTP on the prediction accuracy of FF-NN and RBF-NN. Results indicate the performance of both Neural Networks is improved by decreasing the LTP but the gain achieved in accuracy is not linear and appears to diminish as LTP is reduced from 168 hours to 10 and 5 hours. No considerable improvement is achieved by going lower than LTP=10. The results also show that RBF-NN remains more accurate than FF-NN. The more important observation is that although using a shorter LTP appears to improve the prediction error for both networks, it also appears to be less effective as a strategy to smooth out the seasonal influence for FF-NN. In comparison, the performance of RBF-NN not only becomes much better when reducing LTP but seasonal influences on the error of prediction are also damped.





Figure 4-8 shows the effect of using different combinations of meteorological data at the input layer when predicting wind speed. Results show that combining wind speed training data with other meteorological parameters (e.g. wind speed and solar irradiance) appears to improve predictions and reduce seasonal effects.



Figure 4-8: The effect of prediction parameters on the accuracy of wind speed predicted via FF-NN over the years 2007-2009 (LTP=10 hours). Different combinations of (historical) meteorological data are used as inputs when attempting to predict wind speed. Hourly resolved data is used in training the Neural Network.

4.5 DISCUSSION

Five main observations can be drawn from this study. Firstly, increasing the size of the historical training data set has an insignificant impact on the prediction accuracy of FF-NN and RBF-NN. While the performance of FF-NN minimally improves by using wind speed training data of multiple years, RBF-NN gains no benefit from using more than one year of training data. The reason behind this may be because even a single year (well resolved) wind speed data captures the seasonal effects.

Secondly, FF-NN and RBF-NN both exhibit better performance when trained using hourly wind speed, compared to 0.5, 2 or 3hours. This unexpected behaviour indicates that an intermediate temporal resolution should be targeted, rather than very small or large time resolution. This is believed to indicate that low temporal resolutions (e. g. 2 or 3 hourly) unnecessarily smooth the data and make it harder for the Neural Networks to be adequately trained. Similarly, extremely high resolutions (e. g. 0.5 hours) are inherently susceptible to much variation which also negatively impacts prediction accuracy. To confirm this hypothesis, the standard deviations of the training sets used in this study are calculated and the results depicted in Figure 4-9. The data shows that half hourly resolved data has a significantly higher variability compared to the other data. This relationship was similarly reflected in predictions (Figure 4-5). Further statistical analysis is performed on the differently resolved wind speed data using an F-test. Results, not shown here, indicate that half hourly resolved wind speed data and the other temporal resolutions (1, 2 and 3 hours) do come from normal distributions but

with different variances indicating significant spread between the different data. This result highlights the significance of appropriately selecting (temporal) resolution.



Figure 4-9: Standard deviations of the wind speed training data with different resolutions.

Thirdly, the seasonal variation of wind speed affects the prediction accuracy of a Neural Network, but the severity of this effect is dependent on the prediction methodology deployed. In this regard, the superiority of RBF-NN in wind speed prediction could be attributed to its "architecture". RBF-NN has the capacity to allocate specific hidden neurons to different ranges of wind speed which span the entire dynamic range represented through meteorological data (in this study mostly 3 to 9 m/s). This allows RBF-NN to map finite ranges within the data (e.g., wind speed) to specific neurons in the hidden layer. However, because these allocations are done in the hidden only (not the input layer), this does not affect the time-series nature in the data.. In contrast, the hidden layer of FF-NN tries to find a global approximation that fits the entire dynamic range of input data which is difficult to achieve because of the high nonlinearity in wind speed. As can be seen from Figure 4-10, the magnitude of wind speed varies between 3 m/s and 9 m/s during summer season while this range reduces during winter between 3 m/s and 7 m/s. Also notable here is the striking resemblance between the seasonal variations of wind speed (Figure 4-10) and the errors in the predicted wind speed already presented.



Figure 4-10: Measured hourly wind speed for the years 2001-2009.

The fourth outcome of this research is that reducing the LTP initially increases the prediction accuracy of the wind resource (Figure 4-7), for both Neural Network methodologies used, but the degree of improvement in accuracy appears to plateau as LTP is reduced. Table 4-2 also presents the training time for each methodology used when the LTP is varied between 5 and 168 hours. This data indicates that another merit associated with using a shorter LTP is to improve the time needed to train a Neural Network when predicting the wind resource. This behaviour results because decreasing the LTP reduces the number of neurons in the input layer (Figure 4-3) which means less time is needed to update the connection weights between the input and hidden layer. The physical significance of this is the network is also better able to predict seasonal variations.

Table 4-2: Training time for different Neural Networks based on different lengths oftraining data for wind speed: 5, 10, 60 and 168 hours.

Network	Time to train Neural Network (seconds)							
	LTP=1hours	LTP=10 hours	LTP=60 hours	LTP=168hours				
FF-NN	2,025	2,689	8,003	22,095				
RBF-NN	19	21	94	306				

The fifth outcome is that incorporating (historical) solar irradiance data along with wind speed, during the training phase, can reduce the prediction error of wind speed in some, but not all, Neural Networks (Figure 4-8) and that as shown in Table 4-3 this improvement comes with no negative consequences on the training time of both Neural Networks tested. The physical explanation of this is the Neural Network is better able to discern an (hourly) relationship between the wind speed and the solar irradiance which
then allows the Neural Network to better learn the behaviour of wind speed over prolonged periods spanning multiple seasons. To demonstrate the improvements in prediction accuracy which results from including solar irradiance data, the Absolute Percentage Error (Equation 4.5) is first derived for each (hourly) data point by comparing between the predicted and real value of wind speed. The median of APE's of all the test data (2007-2009) is then derived to show the overall prediction accuracy. Table 4-3 shows the MAPE for both Neural Networks. These results indicate that for FF-NN, incorporating solar irradiance data when predicting wind speed improves the overall accuracy of the network. Regarding RBF-NN, the overall accuracy is not much affected but this maybe because this network has already reached "high" accuracy and there is no further improvement in accuracy in accuracy when historical training data includes both wind speed and solar irradiance.

 Table 4-3: Training time and MAPE for different Neural Networks based on the selection of various parameters for the input layer (LTP=10 hours) over years 2007-2009.

Network	Data input (historical)					
	Wind speed		Wind speed and direction		Wind speed and solar irradiance	
	Time (seconds)	Median of MAPE	Time (seconds)	Median of MAPE	Time (seconds)	Median of MAPE
FF-NN	2689	2.25%	2134	1.5%	2631	1.36%
RBF-NN	21	0.16%	18	0.33%	21	0.24%

The impact of Neural Network training methodology (type of Neural Network and LTP) on the predictions, resolved over different bands across the dynamic range of wind turbine cut-in (2.5 m/s) cut-out speed (11 m/s), is given in Figure 4-11 for two wind turbines (2kW and 30kW). These results indicate that using smaller LTP (10 hours) significantly reduces the prediction error of the generated power across all wind speeds and that more than a 30% improvement in wind power prediction accuracy can be achieved when 10 hours LTP is used instead of 60 or 168 hours. Figure 4-11(a and b) also show that for all LTPs, the power prediction accuracy appears to improve at the higher wind speeds. The reason behind that may be because of the nonlinear shape of the wind turbine power curves (Figure 4-1). According to Lange [38], the shape of the wind turbine's power curve influences the power prediction error. In the steep part of

the wind turbine characteristic curve, a small difference in the wind speed is transferred to relatively larger difference between the corresponding predicted and measured power due to the power law dependency between wind speed and convertible kinetic energy.



Figure 4-11: The power prediction error via FF-NN using different LTP over the years 2007-2009: (a) 2kW turbine; (b) 30kW turbine. Hourly resolved data is used in training the Neural Network.

Figure 4-12 similarly shows that incorporating wind direction or solar irradiance adds further improvement to the prediction accuracy of the generated wind power particularly as the rated speed of each wind turbine is approached (9-11 m/s). At low wind speeds, the improvement in prediction accuracy is either negligible or low compared to higher wind speeds. This indicates that the prediction accuracy of Neural Networks can also be affected by the type of input parameters used and the relative improvement also changes with wind speed.

Since solar irradiance can be predicted to some extent for any location via models such as the ASHRAE [29], the use of multi-parameter predictions using Neural Networks have an advantage over those based solely on wind speed. Solar irradiance incorporated into wind speed predictions could also be a reasonable alternative to other meteorological data which must be measured such as humidity, temperature and pressure.



Figure 4-12: The power prediction error via FF-NN using different training parameters over the years 2007-2009 (LTP=10 hours). Hourly resolved data is used in training the Neural Network.

4.6 CONCLUSIONS

In this paper, the impact of the Neural Network training methodology employed to forecast short-term wind energy is investigated. The research has analysed the effects on prediction accuracy as a consequence of using different size and resolution of training data as well as the LTP employed. In addition, the effects of these parameters on improving the seasonal prediction error for wind speed and the inclusion of solar irradiance (as a training parameter) on prediction accuracy have also been analysed. Two Neural Networks (FF-NN and RBF-NN) have been trained using one and six years' worth of meteorological wind speed data with half hourly, hourly, two hours and three hours temporal resolution to span the training history (5, 10, 60, and 168 past hours). The research has also looked at the effects of predicting wind speed using only wind speed data as well as wind speed with direction and wind speed with solar

irradiance. To assess the impact of Neural Network training methodology on the total power predicted, the power characteristic curves of two commercially available wind turbines have been used.

This paper has found that provided historical meteorological data already spans all seasons (i. e., at least a single year), no significant improvement is achieved by training the networks over more than one year. The results also reveal that seasonal variations can appreciably affect the accuracy of short-term wind speed predictions. The severity of this detrimental influence depends very much on the methodology used. This research has also shown that reducing the length of training data used in Neural Networks improves the accuracy of wind speed prediction and also reduces training time. However, this benefit appears to diminish below a certain value of LTP. The last finding of this study is that incorporating solar irradiance data can improve the prediction accuracy of wind speed with no significant consequences on the training time. This improvement in accuracy appears to be more effective at higher speeds compared to low (cut-in) speeds of the wind turbines. More work is warranted to determine if the outcomes from this research, which are based on the specific Neural Network architectures used (e.g., types, temporal resolution of data, etc), are also applicable to other data sets of wind speed and geographical locations. Unlike other meteorological data, solar irradiance can be easily predicted for geographical locations using well established models such as ASHRAE. This approach of including solar irradiance data when predicting wind speed can help improve estimates of generated wind power at any particular location, especially for remote areas where a record of other meteorological data may not be available. Accurately predicting power generated can help reduce the intermittency associated with wind energy through appropriate sizing and optimisation of energy system component selection. This may also help better size energy storage media such as batteries or hydrogen. Further work needs to be undertaken to explore the effect of using multiple input parameters on the prediction of other renewable resources (such as solar-PV) as well as the impact of using Neural Networks on the ability to meet load requirements in wind energy systems.

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4.8 **REFERENCES**

- [1] Global Wind Energy Council, "Global wind report: Annual market update 2011," 2011.
- H. Lund and B. V. Mathiesen, "Energy system analysis of 100% renewable energy systems—The case of Denmark in years 2030 and 2050," *Energy*, vol. 34, pp. 524-531, 2009.
- [3] H. Lund, "Large-scale integration of wind power into different energy systems," Energy, vol. 30, pp. 2402-2412, 2005.
- [4] A. U. Haque and J. Meng, "Short-term wind speed forecasting based on fuzzy ARTMAP," *International Journal of Green Energy*, vol. 8, pp. 65-80, 2011.
- [5] S. S. Soman, H. Zareipour, O. Malik, and P. Mandal, "A review of wind power and wind speed forecasting methods with different time horizons," in *42nd North American Power Symposium* Arlington, USA, 2010, pp. 1-8.
- [6] W. Xiaomei, W. Fushuan, H. Binzhuo, P. Xiangang, and H. Jiansheng, "Radial basis function neural network based short-term wind power forecasting with Grubbs test," in *4th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*, Weihai, China, 2011, pp. 1879-1882.
- [7] N. Abdel-Karim, M. Small, and M. Ilic, "Short term wind speed prediction by finite and infinite impulse response filters: A state space model representation using discrete Markov process," in *IEEE PowerTech* Bucharest, Romania, 2009, pp. 1-8.
- [8] M. K. Deshmukh and S. S. Deshmukh, "Modeling of hybrid renewable energy systems," *Renewable and Sustainable Energy Reviews*, vol. 12, pp. 235-249, 2008.
- [9] G. Sideratos and N. D. Hatziargyriou, "Probabilistic wind power forecasting using radial basis function neural networks," *IEEE Transactions on Power Systems*, vol. 27, pp. 1-9, 2012.
- [10] G. Reikard, "Using temperature and state transitions to forecast wind speed," Wind Energy, vol. 11, pp. 431-443, 2008.
- [11] L. Wu, J. Park, J. Choi, J. Cha, and K. Y. Lee, "A study on wind speed prediction using artificial neural network at Jeju Island in Korea," in *Transission* and Distribution Conference and Exposition: Asia and Pacific (T&D Asia), Seoul, Korea, 2009, pp. 1-4.
- [12] A. More and M. Deo, "Forecasting wind with neural networks," *Marine Structures*, vol. 16, pp. 35-49, 2003.

- [13] J. Shi, W. J. Lee, Y. Liu, Y. Yang, and P. Wang, "Short term wind power forecasting using hilbert-huang transform and artificial neural network," in 4th International Conference on Electric Utility Dereulation and Restructuring and Power Technologies, Beijing, China, 2011, pp. 162-167.
- [14] A. Anvari Moghaddam and A. Seifi, "Study of forecasting renewable energies in smart grids using linear predictive filters and neural networks," *IET Renewable Power Generation*, vol. 5, pp. 470-480, 2011.
- [15] M. G. De Giorgi, A. Ficarella, and M. Tarantino, "Assessment of the benefits of numerical weather predictions in wind power forecasting based on statistical methods," *Energy*, vol. 36, pp. 3968-3978, 2011.
- [16] Y.-Y. Hong, H.-L. Chang, and C.-S. Chiu, "Hour-ahead wind power and speed forecasting using simultaneous perturbation stochastic approximation (SPSA) algorithm and neural network with fuzzy inputs," *Energy*, vol. 35, pp. 3870-3876, 2010.
- [17] U. Cali, B. Lange, J. Dobschinski, M. Kurt, C. Möhrlen, and B. Ernst, "Artificial neural network based wind power forecasting using a multi-model approach," in 7th International Workshop on Large Scale Integration of Wind Power and on Transmission Networks for Offshore Wind Farms, Madrid, Spain, 2008, pp. 1-6.
- [18] L. J. Ricalde, G. A. Catzin, A. Y. Alanis, and E. N. Sanchez, "Higher order wavelet neural networks with kalman learning for wind speed forecasting," in *IEEE Symposium on Computational Intelligence Applications in Smart Grid* Paris, France, 2011, pp. 1-6.
- [19] S. Li, D. C. Wunsch, E. A. O'Hair, and M. G. Giesselmann, "Using neural networks to estimate wind turbine power generation," *IEEE Transactions on Energy Conversion*, vol. 16, pp. 276-282, 2001.
- [20] G. Kariniotakis, G. Stavrakakis, and E. Nogaret, "Wind power forecasting using advanced neural networks models," *IEEE Transactions on Energy Conversion*, vol. 11, pp. 762-767, 1996.
- [21] R. L. Welch, S. M. Ruffing, and G. K. Venayagamoorthy, "Comparison of feedforward and feedback neural network architectures for short term wind speed prediction," in *International Joint Conference on Neural Networks*, Atlanta, USA, 2009, pp. 3335-3340.
- [22] Y. L. Tu, T. J. Chang, C. I. Hsieh, and J. Y. Shih, "Artificial neural networks in the estimation of monthly capacity factors of WECS in Taiwan," *Energy Conversion and Management*, vol. 51, pp. 2938-2946, 2010.

- [23] K. Bhaskar and S. Singh, "AWNN-Assisted wind power forecasting using feedforward neural network," *IEEE Transactions on Sustainable Energy*, vol. 3, pp. 306-315, 2012.
- [24] M. Kolhe, "GA-ANN for short-term wind energy prediction," in *Power and Energy Engineering Conference* Wuhan, China, 2011, pp. 1-6.
- [25] BOM. (2012, July 18, 2012). *Climate Glossary*. Available: http://www.bom.gov.au/climate/glossary/seasons.shtml
- [26] Anhui Hummer Dynamo Co. Ltd. (2015, 05.07.2012). *Hummer*. Available: http://www.china-windturbine.com/about.htm
- [27] G. Genç, M. Çelik, and M. Serdar Genç, "Cost analysis of wind-electrolyzer-fuel cell system for energy demand in Pınarbaşı-Kayseri," *International Journal of Hydrogen Energy*, vol. 37, pp. 12158-12166, 2012.
- [28] R. Belfkira, G. Barakat, T. Nicolas, and C. Nichita, "Design study and optimization of a grid independent wind/PV/Diesel system," presented at the 13th European Conference on Power Electronics and Applications, Barcelona, Spain, 2009.
- [29] R. Wagner, M. Courtney, J. Gottschall, and P. Lindelöw-Marsden, "Accounting for the speed shear in wind turbine power performance measurement," *Wind Energy*, vol. 14, pp. 993-1004, 2011.
- [30] D. Bechrakis and P. Sparis, "Simulation of the wind speed at different heights using artificial neural networks," *Wind Engineering,* vol. 24, pp. 127-136, 2000.
- [31] M. Ray, A. Rogers, and J. McGowan. (2006, June 2013). Analysis of wind shear models and trends in different terrains. University of Massachusetts, Department of Mechanical and Industrial Engineering, Renewable Energy Research Laboratory. Available: <u>http://www.umass.edu/windenergy/publications/published/2006/AWEA%202006</u> %20Wind%20Shear.pdf
- [32] K. Bakirci, "Estimation of solar radiation by using ASHRAE clear-sky model in Erzurum, Turkey," *Energy Sources, Part A*, vol. 31, pp. 208-216, 2009.
- [33] L. Wong and W. Chow, "Solar radiation model," *Applied Energy,* vol. 69, pp. 191-224, 2001.
- [34] BOM. (2012, July 18, 2012). Daily global solar exposure. Available: <u>http://www.bom.gov.au/jsp/ncc/cdio/weatherData/av?p_nccObsCode=193&p_di</u> <u>splay_type=dailyDataFile&p_stn_num=009264&p_startYear=</u>
- [35] Z. Fengming, C. Kyeonghee, C. Jaeseok, L. Young-Mi, and K. Y. Lee, "A study on wind speed prediction using artificial neural network at Jeju Island in Korea

II," in *IEEE 54th International Midwest Symposium on Circuits and Systems*, Seoul, Korea, 2011, pp. 1-4.

- [36] A. Öztopal, "Artificial neural network approach to spatial estimation of wind velocity data," *Energy Conversion and Management*, vol. 47, pp. 395-406, 2006.
- [37] T. Xie, H. Yu, and B. Wilamowski, "Comparison between traditional neural networks and radial basis function networks," in *International Symposium on Industrial Electronics (ISIE)*, Gdansk, Poland, 2011, pp. 1194-1199.
- [38] M. Lange, "On the uncertainty of wind power predictions-Analysis of the forecast accuracy and statistical distribution of errors," *Transactions of the ASME-N-Journal of Solar Energy Engineering*, vol. 127, pp. 177-184, 2005.

5 CHAPTER 5: PREDICTIVE POWER MANAGEMENT STRATEGIES FOR STAND-ALONE HYDROGEN SYSTEMS: LAB-SCALE VALIDATION

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5.1 ABSTRACT

Power Management Strategies (PMSs) to control stand-alone energy systems affect the reliability of meeting load demand as well as the cyclic operation of various subsystems. The hybridisation of sources through the integration of hydrogen fuel cells with energy storage means optimising the PMS should be "intelligently" done unless relying on rule-based PMSs which are simplistic to use but subject to lack of optimisation. This paper presents the methodology and validation of a lab-scale (desktop) energy system controlled by a predictive PMS. Validation of the intelligently based PMS can be done in the lab-scale before (costly) full deployment in the field, but experiments to support this have not been reported in relation to hydrogen systems. The experimentally tested hybrid energy system consists of an emulated renewable power source which can represent solar-PV and/or wind generators, battery bank and PEM fuel cell integrated with metal hydride storage. Experimental testing as well as the use of real-time predictions using Neural Networks is utilised. The effects of several control parameters which are either hardware dependant or affect the predictive algorithm are investigated with system performance, under the predictive PMS, benchmarked against a rule-based PMS. The results reveal that a predictive PMS is impacted by the prediction horizon used to forecast the availability of renewables or load, the decision time interval used for updating the PMS as well as time lags resulting from hardware sensors used to convey system status to the decision algorithm responsible for updating the PMS. The maximum thresholds of the abovementioned control parameters are 120, 15 and 3 seconds, respectively. Beyond these limits, the ability of the predictive PMS to effectively control the system degrades significantly. This study demonstrates the feasibility of using real-time predictions of renewable

resources and load demand to optimise a PMS in a stand-alone energy system and experimentally validates this, which has not been previously reported.

5.2 INTRODUCTION

Rapidly growing power consumption, climate change and depletion of fossil fuel reserves has increased interest in renewable power generation. In localities where connection to a public power grid may be unavailable or infeasible, wind, solar power, or even diesel generators are options for supplying electric power [1]. If renewably powered, typical application scenarios for such stand-alone (off-grid) systems include serving remote communities [2], powering water desalination [3] and supplying telecommunication stations [4]. However, due to the intermittent and unpredictable nature of wind and solar power, these systems also include energy storage media to ensure reliable and continuous power supply. Recent hydrogen and other hybrid system designs [5-7] rely on batteries for short-term energy storage whilst hydrogen can also be used for long-term energy storage.

The use of hydrogen fuel cell technology in stand-alone applications as a back-up, which provides instant and uninterruptible power when the main power sources are not available or unable to meet the power demand has found a remarkable area in the literature. Mezzai et al presented the modelling of Solar-PV/Wind/Fuel cell hybrid system [8]. A performance analysis of Solar-PV/Fuel cell and Solar-PV/Fuel cell/Battery hybrid systems has been performed by Rekioua et al [9] and Bruni et al, respectively. Behzadi and Niasati analysed different PMSs for stand-alone Solar/PV/Fuel cell/Battery system [10]. Sizing and economic analysis of Wind/Fuel cell [11, 12], Wind/Solar-PV/Fuel cell [11, 13], Solar-PV/Fuel cell [14-16], Solar-PV/Fuel cell/Battery [17] and Wind/Solar-PV/Fuel cell/Battery [18] hybrid systems are also conducted by researchers. However, the above mentioned studies include simulation based analysis with the effect of fuel cells transients ignored, and none of them presents the experimental application of the analysed system.

The hybridisation of renewable power technologies and energy storage complicates the system architecture and increases the cost to design, build and operate these systems. To design reliable and cost-effective (renewably powered) systems, historical time series of resources such as solar and wind as well as load demand profiles are needed. Whilst consideration of total power demand and the availability of renewables can assist in deploying effective methodologies to meet power requirements, an optimised PMS can also help reduce overall cost (\$/kW-hr) [19] as well as improve load

meeting reliability. A PMS typically affects overall performance via determining the control set points to activate/deactivate various energy system components. Because measured profiles of renewable energy resources such as wind may not always be available, especially for remote locations, a PMS that is able to predict (in real-time) the availability of renewables and load demand is highly desirable but challenging to obtain. Therefore in most instances, recourse to several (off-line, not real-time) methods is used to forecast renewable resources using techniques such as Neural Networks (NNs) [20] or the ASHRAE clear-sky model [21].

In relation to sizing of hybrid renewable energy systems, probabilistic [22-24], analytical [25, 26], iterative [27] and hybrid [28] methods have been used. Optimisation of rulebased PMSs [17, 29-31] using algorithms based on if-else statements has also been coupled with intelligent search techniques such as Genetic Algorithm [32, 33] and Particle Swarm Optimisation [34]. However, in most studies the control parameters used in the rule-based PMS have predefined thresholds. This makes rule-based PMSs rigid and not able to adapt to real-time system conditions. Although research into rule-based PMSs is well established in the context of stand-alone systems, little work has been reported to evaluate the performance of intelligent PMSs used for the real-time operation of hybrid renewable energy systems. An intelligent PMS uses techniques such as fuzzy logic [35] and NNs [36, 37] to further predict process parameters and then control the switching of the energy system components such as batteries and fuel cells.

Additionally, whilst simulations have been extensively used to evaluate the performance of PMS applied to hydrogen and other hybrid energy systems, most studies do not include an experimental validation (or real-time testing) due to the challenges involved with the construction of a hybrid power system and the developments of suitable power electronic interfaces [38]. Moreover, no validation of a NN-based predictive PMS has been reported which includes the forecasting of renewables such as wind, and electric loads.

The contribution of this paper focuses on the validation of a NN-based PMS whereby the NN is used to predict the future levels of the controlling parameters. The paper also demonstrates this predictive methodology via experimental validation when the intelligent PMS uses real-time predictions of load demand and renewable power as decision variables. To help benchmark this predictive PMS, results are compared to a rule-based PMS. Moreover, the effect of software related parameters such as the Prediction Horizon (PH) used by the NN to forecast renewables or load demand, as well as the Decision Interval (DI) used by the algorithm to update the control set points within the PMS and hardware related parameters (such as sensor response speed delay) are evaluated. The experimental validation of the (NN) predictive PMS is demonstrated by applying it to a lab-scale (desktop) hybrid energy system. This system consists of an emulated renewable power primary source, energy storage (batteries) and fuel cell (primary mover) for providing back-up during periods where a mismatch appears between renewables and load. Real-time testing is done using a lab-scale fuel cell rather than relying on representative models which is the approach previously reported [39].

This paper is organised as follows. Section 5.3 presents a description of the experimental setup. Section 5.4 explains the predictive and rule-based PMSs tested and Section 5.5 explains the employed reliability index. The results and discussion are presented in Section 5.6 while conclusions are drawn in Section 5.7.

5.3 SYSTEM DESCRIPTION

A typical stand-alone hybrid energy system, shown in Figure 5-1, may consist of a wind turbine, solar-PV panels and other power sources such as fuel cell (or diesel generator set) and battery storage. In such a scenario, the wind turbine and solar-PV panels constitute the primary power source whereas batteries are used for storing the possible excess energy during low demand periods or where excess renewables exist and to absorb short-term fluctuations of the renewable sources so as to avoid frequent start/stop cycles for the fuel cell system [31].



Figure 5-1: A typical (real) stand-alone hydrogen energy system which uses a PMS.

The role of the prime mover fuel cell system (or diesel generator set) is to then supply additional loads beyond the capacity of renewables and batteries. The necessary hydrogen for operating the fuel cell is stored in hydrogen canisters. On-site hydrogen production, using excess power production of primary renewable sources, has drawn significant attention recently [40, 41] and even coupled with renewably powered desalination [34]. In a hybrid renewable energy system, a monitoring and control system is also used and typically comprises a data-acquisition unit and set of sensors needed to real-time monitor and measure both meteorological data (e.g. humidity, temperature, wind speed, solar irradiance, etc.) and operational parameters (voltages and currents of the power generation components) [42]. The number of sensors needed to monitor and control the operation of hybrid energy system depends on the structure and complexity. Studies reported in the literature indicate that the minimum number of sensors needed corresponds to the number of main decision variables involved in the PMS [43-45]. In a lab-scale setup, such (real-time) hybridised energy system may be assembled as shown in Figure 5-2. The setup consists of a total 0.14kW (emulated) renewable power source, 1.2kW fuel cell unit and 0.408kWh battery bank. The system components are collaboratively supplying a dynamic DC load through a common DC bus in a stand-alone mode. The renewable sources (will be referred as primary power source) and fuel cell unit are connected to the DC bus via DC/DC

converters while the battery bank is directly connected to the DC bus through a power relay. The load module is directly connected to the DC bus. The LabVIEW and MATLAB software are used to code the implemented predictive PMS on a laptop computer which has been connected to the energy system via National Instruments (NI) controller interface. Eight sensors are used for the operational parameters of the system setup which include the currents and voltages of the primary power source, battery bank, fuel cell unit and load module. In the following subsections, the hardware components of the considered system are described.



Figure 5-2: The lab-scale (desktop) stand-alone hydrogen energy system used to test the (NN) predictive PMS.

5.3.1 Primary power source (renewables)

Due to the limitations on solar and wind energy availability in a laboratory environment, the renewable power source that used for the stand-alone system tested is emulated using a DC power supply. To simulate the fluctuations of real renewable power source, the output power is steeply changed between zero and full capacity levels of the available DC power supply.

5.3.2 Hydrogen energy system (fuel cell, hydrogen canisters)

In this study, the Nexa 1200 Proton Exchange Membrane (PEM) fuel cell system from Heliocentris [46], is used as a backup. This fuel cell is designed as an air cooled stack equipped with all the necessary peripheral components (fan, compressor, etc.) to ensure stable and safe operation. The rated capacity of stack is 1.2kW and the output voltage varies between 20 and 36V with 65A maximum. The purity of the hydrogen used to operate the PEM fuel cell stack should be 99.95% or better [47]. The hydrogen

gas needed for the operation of the fuel cell system is stored in metal hydride canisters which is an ideal choice for stand-alone applications [48]. A set of three hydrogen canisters of Ovonics Company are utilised for the test bench. Each canister has a weight of 6.5kg and a volume of 760STD litres.

5.3.3 Lead acid battery bank and model

A battery bank consisting of two lead acid batteries is used for absorbing short-term fluctuations of the renewable power source. Each battery has electrical specifications of 12V and 17Ah. The Battery State-Of-Charge (B_{SOC}) is an important parameter for systems that include batteries as an energy storage not only to estimate the amount of energy stored, but also to avoid over charging/discharging to protect the battery from damage [49]. The B_{SOC} is also important for implementing effective PMSs for hybrid renewable energy systems [50, 51]. However, the measurement of the B_{SOC} is a challenging task because of the complexity determining the battery's available energy [52]. Several methods have been proposed to monitor the B_{SOC}. Examples include open-circuit voltage, specific gravity and constant load methods [52]. The aforementioned methods are not suitable for online and continuous monitoring, as required in hybrid renewable energy systems, because they require long stabilisation period [52]. For lead acid batteries, B_{SOC} is linearly proportional to its discharge voltage [49, 53]. Therefore, in this work, the battery's terminal voltage is used as an approximation of the B_{SOC}. The predictive PMS uses a model for the utilised battery bank to estimate (future) charging/discharging dynamics. While many models are available in the literature [54, 55], a simple model for a rechargeable lead acid battery is used. The model is based on the following equation [56]:

$$V_b = (1 - \delta) * V_{con} - K * Q_{max} * (1 - B_{SOC}) / B_{SOC}$$
5.1

In this regard, V_b is the battery's terminal voltage (V), V_{con} is the battery's constant voltage (V), K is the polarisation resistance (Ω) and δ is the voltage drop during discharging expressed as a fraction of the battery constant voltage. When the battery is charging, the voltage drop (δ) is zero. The B_{SOC} is computed by the integration of the battery current, *i*, according to the following:

$$B_{SOC} = 1 - (1/Q_{max}) * \int i(t) dt$$
 5.2

In the above equation, Q_{max} is the battery's maximum capacity (Ah). To incorporate the battery model into the predictive PMS, the model is simulated using MATLAB/SIMULINK software and its parameters are firstly optimised (using measured data) with the help of Simulink Design Optimisation toolbox. For this purpose,

charging/discharging experiments at three constant currents (4, 7 and 12 A) have been conducted on the battery bank described earlier. The optimised battery model is then converted into a Dynamic Link Library (DLL) in order to incorporate it into the predictive PMS which is coded in the LabVIEW software environment, thanks to the LabVIEW Model Interface Toolkit (MIT).

5.3.4 Load module and power conditioning units

An electronic DC load unit, which is supplied by Heliocentris [46], is utilised in the system. This electronic load can work in variable current and power modes and can be controlled manually or by a computer. The employed load module has a maximum power of 1.5kW, maximum current of 100A, and operating voltage ranges from 1 to 75V. As the available load is a DC load, a DC/AC inverter unit is not used for power conditioning. An inverter should be included if the system is integrated to supply an AC load. Because the implemented test bench has one common 24V DC bus, two DC/DC converters, which are power electronic devices that enable matching the output voltages of different energy sources to work together on the same DC bus, are used to regulate the output voltage of the primary power source and PEM fuel cell stack. The specifications of the utilised converters are listed in Table 5-1 [57].

DC/DC converter	Primary power source side	PEM fuel cell side
Rated power (W)	100.8	504
Input voltage (V)	36-72	19-72
Output voltage (V)	24	24
Maximum current (A)	4.2	21

Table 5-1: Technical characteristics of the DC/DC converters

5.3.5 Data acquisition, controller and sensors

The NI reconfigurable embedded monitoring and control system (NI cRIO-9047) is used to acquire measurements from and send control signals to the system. This unit is programmed with LabVIEW programming tools and can be used in a variety of applications by using several input and output modules. In this work, the NI-9477 digital output module is employed to transfer the control signals from the laptop computer to the power relay used to connect/disconnect the battery bank to the DC bus, and to start/stop the fuel cell unit. The NI-9221 analogue input module is used for voltage measurements while NI-9205 analogue input module along with four Hass-100s Halleffect current transducers are used for current measurements. The signals sensed by the current transducers are calibrated to correspond to their original physical units using the following calibration equation [42]:

$$y_i = a_i \cdot x_i + b_i \tag{5.3}$$

In this regard, y_i is the *i*th sensor output in physical units, x_i is the *i*th measured sample. a_i and b_i are calibration coefficients and their values are experimentally derived. The speeds at which the sensors respond to the changes of the system status control how fast the PMS reacts to these changes. If there is a delay in the sensor's response, this may affect the ability of the PMS to properly control the stand-alone system. In this study, the effect of the Sensor Delay (SD) on the performance of the predictive PMS is investigated by imposing an artificial time lag on the measured voltages and currents across some of the system components.

5.3.6 Renewables and load demand prediction

As mentioned earlier, the predictive PMS uses real-time predictions of load demand and renewable power to decide the switching of the battery bank and fuel cell unit. NNs are widely used for prediction applications such as wind energy [20], electric loads [58] and solar irradiance [59]. A previous study by the authors of this paper has proven that Radial Basis Function Neural Networks (RBF-NNs) are good forecasting tools for nonlinear time series dynamics [20]. Therefore, a RBF-NN is used in this work for realtime prediction of the load demand. The load profile used to test the experimental setup is used to train RBF-NNs to perform 30, 40, 50, 60 and 120seconds ahead PH. The procedure that is used to train the RBF-NNs has been explained by the author in an earlier work [20]. More details about the structure, activation function and advantages of RBF-NN can also be found in the mentioned work. Because the renewable power source is emulated using DC power supply, predictions of (future) renewable power are assumed available. The load demand prediction error is expressed as the difference between the measured and predicted values as follows:

$$Error(t) = P_{Load}(t) - \hat{P}_{Load}(t)$$
5.4

In the above equation, P_{Load} is the measured load demand and \hat{P}_{Load} is the predicted load demand. The NN toolbox under MATLAB/SIMULINK software is used to realise and train the used RBF-NNs because LabVIEW software, unfortunately, has no NN toolkit. As with the battery model, the trained NN is converted to a DLL and then incorporated into the predictive PMS using the LabVIEW MIT.

5.4 POWER MANAGEMENT STRATEGIES

In stand-alone hybrid energy systems, the objective of PMS is to control the switching of the energy system components in order to satisfy the load demand while maintaining the operation of each component within an acceptable range of technical limitations. In this study, two PMSs have been used for the lab-scale (desktop) stand-alone energy system. Namely: predictive PMS and rule-based PMS. A description for each one is given below.

5.4.1 Predictive PMS

In the predictive PMS employed in this study, the decision to switch the batteries power relay or activate the fuel cell unit is taken prior to an actual power deficit occurs based on predicted (future) value of the load demand and (future) estimation of the output power of the primary power source, and B_{SOC} . The inputs of the PMS are the measured power of the primary power source and measured load demand at time *t*. The measurements of the load demand are sequentially passed to the RBF-NN to predict the expected load demand at t + PH. The difference between the estimated (future) output of the primary power source and predicted load demand is then calculated as follows:

$$\hat{P}_e(t+PH) = \hat{P}_{Primary}(t+PH) - \hat{P}_{Load}(t+PH)$$
5.5

where $\hat{P}_e(t + PH)$ is the estimated net power and $\hat{P}_{Primary}(t + PH)$ and $\hat{P}_{Load}(t + PH)$ are the future estimation of the output power of the primary power source and the predicted load demand, respectively, at t + PH. The estimated net power is then used by the battery model to estimate the future B_{SOC} , $\hat{B}_{SOC}(t + PH)$ which is used along with the estimated net power to define the charging/discharging of the battery bank and the start/stop of the fuel cell unit. Figure 5-3 describes the decision mechanism of the predictive PMS. Minimum and maximum B_{SOC} limits (B_{min} and B_{max} respectively) are imposed on the operation of the battery bank for protection against overcharging as well as over discharging. In this regard, the battery bank is allowed to be discharged to no less than B_{min} and charged to no more than B_{max} . In addition, to protect the fuel cell unit against frequent start/stop cycles, which may harm the fuel cell stack [29], once the stack is activated, it would not be deactivated unless a pre-defined timespan has elapsed (5min in this experiment).





5.4.2 Rule-based PMS

The decision variables for the rule-based PMS are the measured output power of the primary power source, load demand and the B_{SOC} . In this PMS, the output power of the primary power source and the load demand are measured at each time step *t* and the system's net power, P_e , is calculated according to the following:

$$P_e(t) = P_{primary}(t) - P_{Load}(t)$$
5.6

where $P_{primary}$ and P_{Load} are the measured power of the primary power source and load module respectively. The value of the net power and the measured B_{SOC} are then used by the rule-based PMS to generate the proper control signals for the battery bank and the fuel cell unit. As in the predictive PMS, constraints (B_{min} and B_{max} respectively) are imposed on the operation of the battery bank, and the fuel cell unit is kept operating for at least 5 minutes after receiving a start command to avoid frequent start/stop cycles. The decision mechanism for the rule-based PMS is also shown in Figure 5-3.

5.5 RELIABILITY INDEX

To evaluate the reliability of hybrid renewable energy systems, several reliability indices are introduced in the literature [41, 60, 61]. Loss of Power Supply Probability (LPSP), Loss of Energy Expected (LOEE) and Loss of Load Expected (LOLE) are examples of the used indices. Among the aforementioned indices, LPSP has been widely used to evaluate stand-alone (off-grid) renewable energy systems. In this study, a Loss of Load Period (LOLP) index which represents the sum of time steps during which the system cannot supply the whole load demand, is adopted and it is defined as follows:

$$LOLP = \sum_{t=1}^{N} \begin{cases} 1; & P_{primary}(t) + P_{bat}(t) + P_{fc}(t) < P_{load}(t) \\ 0; & otherwise \end{cases}$$
5.7

In the above equation, *N* is the number of time steps in which the system's reliability is evaluated (here, N = 3900 seconds). $P_{bat}(t)$ and $P_{fc}(t)$ are the battery and fuel cell output power, respectively, at time step *t*.

5.6 RESULTS AND DISCUSSION

Each test run (operating condition) on the energy system (Figure 5-2) lasted 65minutes so as to capture system performance and stability across both transient and steady state operation and when subject to the rule-based PMS (Figure 5-3). Figure 5-4a shows the load demand profile applied across test conditions. Whilst this load profile can be varied, it was used throughout this study so as to provide a common basis for comparing between a rigid PMS and predictive PMS. To simulate the intermittency of real renewable energy sources (Figure 5-1), the power from the emulated renewable source (DC power supply) is changed between zero and full capacity levels. The initial conditions for the PMS controlling the power system (at time t = 0) are as follows: $B_{min} = 92\%$ (corresponds to battery terminal voltage of 23 V) and $B_{max} = 100\%$ (corresponds to measured battery voltage at full charge). The initial state of the fuel cell unit (primary mover) is off and the hydrogen canisters (energy storage) are fully charged. Figure 5-4b shows a comparison between the measured and estimated B_{SOC} (measure as terminal voltage of the battery bank). As can be seen from Figure 5-4, the implemented predictive PMS successfully controls the switching of the power system components and the lab-scale stand-alone energy system able to meet demand over

both transient and steady state stages. It can also be seen that the battery model used to predict future B_{SOC} levels closely follows the measured B_{SOC} .





To further evaluate the predictive PMS's performance, software controlling parameters such as the (i) NN Prediction Horizon (PH) and (ii) PMS Decision Interval (DI) are varied and their effect on the reliability for the system to meet the load demand (Figure 5-4a) is analysed. Another controlling parameter investigated is the role of the (iii) Sensor Delay (DS) to respond to changes in power system status which is hardware related. The PH represents the prediction step (in seconds) used by the NN to forecast load demand or available renewable power. The DI represents the time interval (in seconds) at which the predictive PMS makes device switching decisions. In addition, the behaviour of the power system when controlled by the predictive PMS is compared to the same system if controlled by a rule-based PMS. Four main results can be drawn from varying parameters (i)-(iii) from this study.

Firstly, the DI has a gradual effect on the system's reliability to meet the load demand (measured as a LOLP) while the PH has a threshold effect. Figure 5-5 shows a fit of the measured LOLP versus several combinations of DI and PH. Here, the considered values of DI are 1, 15, 30, 45 and 60seconds while PH values are 30, 40, 50 and 60seconds. From this figure it can be seen that for DI less than 15seconds, the stand-alone power system has a maximum reliability and no LOLP has been recorded. As the DI exceeds around 15seconds and up to 60seconds, system reliability gradually decreases even though the predictive PMS is still able to maintain stable operation for the energy system. For up to 60seconds, the PH seems to have no direct influence on system capacity to meet the load demand. However, when the PH is increased to 120seconds, the system becomes unstable with total loss of the load supply. These results do highlight that parameters PH and DI do affect the performance (LOLP) for the system or its overall stability. Whilst some of these parameters have a steady effect (DI), others appear to have more abrupt influence (PH).



Figure 5-5: The effect of the Decision Interval (DI) and Prediction Horizon (PH) on the LOLP of the stand-alone hydrogen energy system. Negative LOLP refers to total loss of supply.

Secondly, the results show that a predictive PMS is highly sensitive to the speed at which the measurement sensors respond to changes in status of the power system. To assess the effect of delays in sensors response, a time lag has been imposed on the

measurements of the decision variables involved in the predictive PMS and its effect on the load meeting reliability (LOLP) is analysed. Figure 5-6 shows the variation in LOLP when 1, 2 and 3seconds time lags are imposed on the SD for the primary power source, load demand and the B_{SOC}. The time lags are applied to the sensors connected to the emulated renewable power source, electronic load and the battery bank. These results show that LOLP increases with increase the SD. Whilst LOLP changes gradually with SD in the range SD=1-3, when SD>3 the predictive PMS failed to control the system with total loss of supply. These results indicate that synchronisation between the PMS and the system hardware has a significant impact on the performance of a predictive PMS. An increased SD means data used to update the status of the predictive PMS via the Neural Network becomes less representative of the dynamics and status of renewable power and load demand. Therefore, it is important to consider the sensor measurement delay when implementing a predictive PMS.





Thirdly, the results show that the stability of a predictive PMS is affected by the forecasting error. Figure 5-7 (a and b) shows the prediction error of the load demand and the control signal of battery power relay, respectively. From this figure it can be seen that the NN prediction error is relatively higher at the load demand transient periods (Here, the load transient refers to the instances when the load demand changes from one level to another). The increase of the prediction error during the load transients makes the predictive PMS sends a frequent open/close commands to the

battery power relay as shown in Figure 5-7b. This makes the system unstable during load transients.



Figure 5-7: The effect of prediction error on the performance of the predictive PMS. (a) Load demand and Prediction error profiles. (b) The control signal of the battery bank power relay. (P_{max} =1.2kW).

Finally, this study has shown that the predictive PMS can help prevent the loss of power supply during the transient start-up time of back-up prime movers (e.g. a fuel cell). Figure 5-8 shows the measured load demand when predictive and rule-based PMSs are used for the energy system. As for the rule-based PMS, 20 seconds LOLP have been observed at the instance when the strategy activated the fuel cell unit to supply the deficit instead of the battery bank. This LOLP has not been observed when predictive PMS is used. The reason may be because the fuel cell has a relatively slow transient response as it is experimentally proven in an earlier work by the authors [41]. Unlike the rule-based PMS, the predictive PMS has the advantage of anticipating the future level of the B_{SOC} and makes an early start of the fuel cell unit which allows the transient start-up time to pass before the fuel cell unit is actually requested to supply power to the load. This advantage of predictive PMSs can be useful in scheduling the operation of the components of the hybrid renewable power systems based on future

availability of renewable resources which may help designing more efficient, reliable and cost-effective hybrid renewable energy systems.





The results of this study verify the effectiveness of using NN-based PMSs for managing the power flow of stand-alone hybrid power systems and investigated the effect of some software and hardware related controlling parameters that affect the performance of this type of intelligent PMSs. Using NNs for controlling the operation of hybrid power systems may allow implementing much more advanced intelligent PMSs that are able to schedule the operation of the power generation components of hydrogen and other hybridised renewable energy systems beforehand based on (future) predictions of the availability of renewable resources. This may result in designing hybrid renewable energy systems less susceptible to the intermittency of renewable resources and able to efficiently utilise the available resources which in turn may increase the reliability and reduce the cost of power generation.

5.7 CONCLUSIONS

This paper presents the construction of a lab-scale (stand-alone) hybrid energy system featuring a hydrogen fuel cell coupled with metal hydride storage satisfying a dynamic load demand. The experimental setup consists of an emulated renewable power source which is considered as a primary source, battery bank and PEM fuel cell unit which is used to supply the deficit power during periods the primary source cannot meet the whole load demand. Besides, an intelligent PMS based on NNs (termed as predictive PMS) is employed to control the overall power flow within the system. In

addition, the performance of the implemented predictive PMS is evaluated by assessing the effect of some software and hardware related controlling parameters. Moreover, a comparison to a rule-based PMS to control the same system is conducted. The Loss of Load Period (LOLP), which represents the sum of time periods during which the setup cannot supply the load demand, is used as an assessment criterion. Results not only validate the use of a predictive PMS to manage the switching of the components in a hydrogen or hybridised energy system but also shed light on how several parameters influence the effectiveness of this approach. The following specific outcomes have been drawn from this study:

- The decision interval of the predictive PMS has a gradual effect on the reliability of the energy systems to meet the load demand while the prediction horizon has a threshold effect. The maximum limits of the decision interval and prediction horizon are 60 and 120seconds, respectively.
- The accuracy of the prediction tool employed to realise the predictive PMS affect the stability of the controlled energy system.
- The predictive PMS is sensitive to the delays of sensors response to the changes of the system conditions. Results showed that more than 3seconds delay will lead to a total loss of load.
- Unlike rule-based ones, predictive PMSs can help prevent the loss of power supply that may occur during the transient start-up time of the back-up power units of hybridised renewable energy systems.

Whilst this study has focused on demonstrating a lab validation and analysis of using predictive PMS with a stand-alone system, further research is warranted into the techno-economic or environmental impact (net present cost, cost of energy, lifetime CO2 emissions) of using a predictive PMS on a hybrid renewable energy system.

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5.9 REFERENCES

- W. Wu, J. Xu, and J. Hwang, "Multi-loop nonlinear predictive control scheme for a simplistic hybrid energy system," *International journal of hydrogen energy*, vol. 34, pp. 3953-3964, 2009.
- [2] Y. Himri, A. B. Stambouli, B. Draoui, and S. Himri, "Techno-economical study of hybrid power system for a remote village in Algeria," *Energy*, vol. 33, pp. 1128-1136, 2008.
- [3] D. P. Clarke, Y. M. Al-Abdeli, and G. Kothapalli, "The effects of including intricacies in the modelling of a small-scale solar-PV reverse osmosis desalination system," *Desalination*, vol. 311, pp. 127-136, 2013.
- [4] J. K. Kaldellis, "Optimum hybrid photovoltaic-based solution for remote telecommunication stations," *Renewable Energy*, vol. 35, pp. 2307-2315, 2010.
- [5] S. Kelouwani, K. Agbossou, and R. Chahine, "Model for energy conversion in renewable energy system with hydrogen storage," *Journal of Power Sources*, vol. 140, pp. 392-399, 2005.
- [6] P. García, J. P. Torreglosa, L. M. Fernández, and F. Jurado, "Improving longterm operation of power sources in off-grid hybrid systems based on renewable energy, hydrogen and battery," *Journal of Power Sources*, vol. 265, pp. 149-159, 2014.
- [7] M. Bielmann, U. Vogt, M. Zimmermann, and A. Züttel, "Seasonal energy storage system based on hydrogen for self sufficient living," *Journal of Power Sources*, vol. 196, pp. 4054-4060, 2011.
- [8] N. Mezzai, D. Rekioua, T. Rekioua, A. Mohammedi, K. Idjdarane, and S.
 Bacha, "Modeling of hybrid photovoltaic/wind/fuel cells power system,"
 International Journal of Hydrogen Energy, vol. 39, pp. 15158-15168, 2014.
- [9] D. Rekioua, S. Bensmail, and N. Bettar, "Development of hybrid photovoltaicfuel cell system for stand-alone application," *International Journal of Hydrogen Energy*, vol. 39, pp. 1604-1611, 2014.
- [10] M. S. Behzadi and M. Niasati, "Comparative performance analysis of a hybrid PV/FC/battery stand-alone system using different power management strategies and sizing approaches," *International Journal of Hydrogen Energy*, vol. 40, pp. 538-548, 2015.
- [11] Y. Kalinci, A. Hepbasli, and I. Dincer, "Techno-economic analysis of a standalone hybrid renewable energy system with hydrogen production and storage options," *International Journal of Hydrogen Energy*, vol. 40, pp. 7652-7664, 2015.

- [12] M. Aguado, E. Ayerbe, C. Azcárate, R. Blanco, R. Garde, F. Mallor, and D. M. Rivas, "Economical assessment of a wind-hydrogen energy system using WindHyGen® software," *International Journal of Hydrogen Energy*, vol. 34, pp. 2845-2854, 2009.
- [13] M. Eroglu, E. Dursun, S. Sevencan, J. Song, S. Yazici, and O. Kilic, "A mobile renewable house using PV/wind/fuel cell hybrid power system," *International Journal of Hydrogen Energy*, vol. 36, pp. 7985-7992, 2011.
- [14] J. Andrews and B. Shabani, "Dimensionless analysis of the global technoeconomic feasibility of solar-hydrogen systems for constant year-round power supply," *International Journal of Hydrogen Energy*, vol. 37, pp. 6-18, 2012.
- [15] H. Tebibel and S. Labed, "Design and sizing of stand-alone photovoltaic hydrogen system for HCNG production," *International Journal of Hydrogen Energy*, vol. 39, pp. 3625-3636, 2014.
- [16] J. Lagorse, M. G. Simões, A. Miraoui, and P. Costerg, "Energy cost analysis of a solar-hydrogen hybrid energy system for stand-alone applications," *International Journal of Hydrogen Energy*, vol. 33, pp. 2871-2879, 2008.
- [17] M. Castañeda, A. Cano, F. Jurado, H. Sánchez, and L. M. Fernández, "Sizing optimization, dynamic modeling and energy management strategies of a standalone PV/hydrogen/battery-based hybrid system," *International Journal of Hydrogen Energy*, vol. 38, pp. 3830-3845, 2013.
- [18] A. R. Prasad and E. Natarajan, "Optimization of integrated photovoltaic–wind power generation systems with battery storage," *Energy*, vol. 31, pp. 1943-1954, 2006.
- [19] S. Vosen and J. Keller, "Hybrid energy storage systems for stand-alone electric power systems: optimization of system performance and cost through control strategies," *International Journal of Hydrogen Energy*, vol. 24, pp. 1139-1156, 1999.
- [20] A. Brka, Y. M. Al-Abdeli, and G. Kothapalli, "Influence of neural network training parameters on short-term wind forecasting," *International Journal of Sustainable Energy*, pp. 1-17, 2014. DOI: 10.1080/14786451.2013.873437.
- [21] L. Wong and W. Chow, "Solar radiation model," *Applied Energy*, vol. 69, pp. 191-224, 2001.
- [22] H. Yang, L. Lu, and J. Burnett, "Weather data and probability analysis of hybrid photovoltaic–wind power generation systems in Hong Kong," *Renewable Energy*, vol. 28, pp. 1813-1824, 2003.

- [23] G. Tina and S. Gagliano, "Probabilistic analysis of weather data for a hybrid solar/wind energy system," *International Journal of Energy Research*, vol. 35, pp. 221-232, 2011.
- [24] G. Tina, S. Gagliano, and S. Raiti, "Hybrid solar/wind power system probabilistic modelling for long-term performance assessment," *Solar Energy*, vol. 80, pp. 578-588, 2006.
- [25] R. Dufo-López, J. L. Bernal-Agustín, and F. Mendoza, "Design and economical analysis of hybrid PV–wind systems connected to the grid for the intermittent production of hydrogen," *Energy Policy*, vol. 37, pp. 3082-3095, 2009.
- [26] D. K. Khatod, V. Pant, and J. Sharma, "Analytical approach for well-being assessment of small autonomous power systems with solar and wind energy sources," *IEEE Transactions on Energy Conversion*, vol. 25, pp. 535-545, 2010.
- [27] M. Sharafi and T. Y. ELMekkawy, "Multi-objective optimal design of hybrid renewable energy systems using PSO-simulation based approach," *Renewable Energy*, vol. 68, pp. 67-79, 2014.
- [28] S. Dehghan, H. Saboori, A. Parizad, and B. Kiani, "Optimal sizing of a hydrogen-based wind/PV plant considering reliability indices," presented at the International Conference on Electric Power and Energy Conversion Systems, Sharjah, United Arab Emirates, 2009.
- [29] D. Ipsakis, S. Voutetakis, P. Seferlis, F. Stergiopoulos, and C. Elmasides, "Power management strategies for a stand-alone power system using renewable energy sources and hydrogen storage," *International Journal of Hydrogen Energy*, vol. 34, pp. 7081-7095, 2009.
- [30] D. Ipsakis, S. Voutetakis, P. Seferlis, F. Stergiopoulos, S. Papadopoulou, and
 C. Elmasides, "The effect of the hysteresis band on power management strategies in a stand-alone power system," *Energy*, vol. 33, pp. 1537-1550, 2008.
- [31] D. P. Clarke, Y. M. Al-Abdeli, and G. Kothapalli, "The impact of renewable energy intermittency on the operational characteristics of a stand-alone hydrogen generation system with on-site water production," *International Journal of Hydrogen Energy*, vol. 38, pp. 12253-12265, 2013.
- [32] R. Dufo-Lopez, J. L. Bernal-Agustín, and J. Contreras, "Optimization of control strategies for stand-alone renewable energy systems with hydrogen storage," *Renewable Energy*, vol. 32, pp. 1102-1126, 2007.

- [33] A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M. Fadali, and Y. Baghzouz,
 "Genetic-algorithm-based optimization approach for energy management,"
 IEEE Transactions on Energy Conversion, vol. 28, pp. 162-170, 2013.
- [34] D. P. Clarke, Y. M. Al-Abdeli, and G. Kothapalli, "The impact of using Particle Swarm Optimisation on the operational characteristics of a stand-alone hydrogen system with on-site water production," *International Journal of Hydrogen Energy*, vol. 39, pp. 15307-15319, 2014.
- [35] S. Sallem, M. Chaabene, and M. Kamoun, "Energy management algorithm for an optimum control of a photovoltaic water pumping system," *Applied Energy*, vol. 86, pp. 2671-2680, 2009.
- [36] A. Hajizadeh and M. A. Golkar, "Intelligent power management strategy of hybrid distributed generation system," *International Journal of Electrical Power* & Energy Systems, vol. 29, pp. 783-795, 2007.
- [37] E. I. Vrettos and S. A. Papathanassiou, "Operating policy and optimal sizing of a high penetration RES-BESS system for small isolated grids," *IEEE Transactions on Energy Conversion*, vol. 26, pp. 744-756, 2011.
- [38] O. Erdinc, O. Elma, M. Uzunoglu, U. Selamogullari, B. Vural, E. Ugur, A. Boynuegri, and S. Dusmez, "Experimental performance assessment of an online energy management strategy for varying renewable power production suppression," *International Journal of Hydrogen Energy*, vol. 37, pp. 4737-4748, 2012.
- [39] M. Secanell, J. Wishart, and P. Dobson, "Computational design and optimization of fuel cells and fuel cell systems: a review," *Journal of Power Sources,* vol. 196, pp. 3690-3704, 2011.
- [40] A. Maleki and A. Askarzadeh, "Comparative study of artificial intelligence techniques for sizing of a hydrogen-based stand-alone photovoltaic/wind hybrid system," *International Journal of Hydrogen Energy*, vol. 39, pp. 9973-9984, 2014.
- [41] A. Brka, Y. M. Al-Abdeli, and G. Kothapalli, "The interplay between renewables penetration, costing and emissions in the sizing of stand-alone hydrogen systems," *International Journal of Hydrogen Energy*, vol. 40, pp. 125-135, 2015.
- [42] E. Koutroulis and K. Kalaitzakis, "Development of an integrated data-acquisition system for renewable energy sources systems monitoring," *Renewable Energy*, vol. 28, pp. 139-152, 2003.

- [43] M. Benghanem and A. Maafi, "Data acquisition system for photovoltaic systems performance monitoring," *IEEE Transactions on Energy Conversion*, vol. 47, pp. 30-33, 1998.
- [44] M. Benghanem, A. H. Arab, and K. Mukadam, "Data acquisition system for photovoltaic water pumps," *Renewable Energy*, vol. 17, pp. 385-396, 1999.
- [45] R. Mukaro and X. F. Carelse, "A microcontroller-based data acquisition system for solar radiation and environmental monitoring," *IEEE Transactions on Energy Conversion*, vol. 48, pp. 1232-1238, 1999.
- [46] Heliocentris. (2015, March 15). *Energy Solutions AG*. Available: <u>http://www.heliocentris.com/</u>
- [47] Ballard Power Systems. (access date: 2014, January 10). Nexa power module user's manual man5100078. Available: http://my.fit.edu/~swood/Fuel%20Cell%20Manual.pdf
- [48] M. Botzung, S. Chaudourne, O. Gillia, C. Perret, M. Latroche, A. Percheron-Guegan, and P. Marty, "Simulation and experimental validation of a hydrogen storage tank with metal hydrides," *International Journal of Hydrogen Energy*, vol. 33, pp. 98-104, 2008.
- [49] M. Coleman, C. K. Lee, C. Zhu, and W. G. Hurley, "State-of-charge determination from EMF voltage estimation: Using impedance, terminal voltage, and current for lead-acid and lithium-ion batteries," *IEEE Transactions on Energy Conversion*, vol. 54, pp. 2550-2557, 2007.
- [50] E. Dursun and O. Kilic, "Comparative evaluation of different power management strategies of a stand-alone PV/Wind/PEMFC hybrid power system," *International Journal of Electrical Power & Energy Systems,* vol. 34, pp. 81-89, 2012.
- [51] A. Bilodeau and K. Agbossou, "Control analysis of renewable energy system with hydrogen storage for residential applications," *Journal of Power Sources*, vol. 162, pp. 757-764, 2006.
- [52] K. Kutluay, Y. Cadirci, Y. S. Ozkazanc, and I. Cadirci, "A new online state-ofcharge estimation and monitoring system for sealed lead-acid batteries in telecommunication power supplies," *IEEE Transactions on Energy Conversion*, vol. 52, pp. 1315-1327, 2005.
- [53] A. H. Anbuky and P. E. Pascoe, "VRLA battery state-of-charge estimation in telecommunication power systems," *IEEE Transactions on Energy Conversion*, vol. 47, pp. 565-573, 2000.

- [54] A. E. S. A. Nafeh, "Optimal economical sizing of a PV-wind hybrid energy system using genetic algorithm," *International Journal of Green Energy*, vol. 8, pp. 25-43, 2011.
- [55] S. Pedrazzi, G. Zini, and P. Tartarini, "Complete modeling and software implementation of a virtual solar hydrogen hybrid system," *Energy Conversion and Management*, vol. 51, pp. 122-129, 2010.
- [56] R. A. Jackey. (2007, April 20). A simple, effective lead-acid battery modeling process for electrical system component selection. SAE Technical Paper. Available: http://papers.sae.org/2007-01-0778/
- [57] MEAN WELL Enterprises Co. Ltd. (2014, April 4). Available: http://www.meanwell.com/
- [58] D. C. Park, M. El-Sharkawi, R. Marks, L. Atlas, and M. Damborg, "Electric load forecasting using an artificial neural network," *IEEE Transactions on Energy Conversion*, vol. 6, pp. 442-449, 1991.
- [59] A. Mellit and A. M. Pavan, "A 24-h forecast of solar irradiance using artificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, Italy," *Solar Energy,* vol. 84, pp. 807-821, 2010.
- [60] A. Kashefi Kaviani, G. Riahy, and S. Kouhsari, "Optimal design of a reliable hydrogen-based stand-alone wind/PV generating system, considering component outages," *Renewable Energy*, vol. 34, pp. 2380-2390, 2009.
- [61] D. Xu, L. Kang, L. Chang, and B. Cao, "Optimal sizing of standalone hybrid wind/PV power systems using genetic algorithms," presented at the Canadian Conference on Electrical and Computer Engineering, Sask, Canada, 2005.

6 CHAPTER 6: PREDICTIVE POWER MANAGEMENT STRATEGIES FOR STAND-ALONE HYDROGEN SYSTEMS: OPERATIONAL IMPACT

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6.1 ABSTRACT

This paper compares the operational impacts of both predictive and reactive Power Management Strategies (P-PMS and R-PMS). The study is implemented for a standalone hybrid system based on wind turbines (WG), batteries (BAT) and hydrogen technology. The P-PMS uses real-time Neural Network (NN) predictions of wind speed and load demand to adjust the control set points affecting the switching of devices. The study also analyses the effects of using another intelligent technique, Particle Swarm Optimisation (PSO), for the real-time optimisation of fuel cell operation. Genetic Algorithms (GA) are used to optimally size the hydrogen system. The research presented in this study is an extension of an earlier work in which the concept of P-PMS was experimentally validated and the effects of some software and hardware related controlling parameters assessed. This paper however goes further by analysing the impact of using P-PMS on the economic and operational characteristics of standalone hydrogen systems by benchmarking it against an R-PMS. Results reveal that a hybrid system operating under a Predictive PMS outperforms that with a reactive PMS in terms of cost, renewables penetration and environmental footprint. However, these merits are realised only if a particularly high reliability of load satisfaction is required. Results also show that a P-PMS highly depends on the accuracy of the employed (NN) prediction tool. The methods employed include MATLAB simulations to implement the three intelligent techniques (GA, NN and PSO) and integration of experimentally derived fuel cell characteristics as well as highly dynamic electric load and wind speed profiles.

6.2 INTRODUCTION

Solar-PV and wind energy systems are hybridised by adding backup prime movers and energy storage media so as to reliably meet electric power even during higher demand periods [1]. Diesel generators [2] and batteries [3] are traditionally used in this context but these are expensive to operate and maintain at remote locations [4], as well as having undesirable environmental impact [5]. Batteries can also suffer from short lifetime and poor reliability [6] which can affect their application in remotely located hybrid systems.

Regardless of the choice for prime movers, designing reliable and cost-effective standalone energy systems is challenging because it often requires considering trade-offs between different performance measures. An effective operational strategy, commonly known as a Power Management Strategy (PMS), is also needed to control device switching and power supply during operation. All these considerations affect the operational impact of the systems (costs, load meeting reliability, CO₂ footprint)

Numerous studies have been undertaken to optimally size different configurations of stand-alone renewable energy systems [7-11]. These sizing methods span singleobjective function methodologies (i.e. minimising only cost [12, 13]) or multipleobjective function methodologies which may consider minimising cost and also reducing environmental footprint [14, 15], shrinking unmet load [16] or dumped excess energy [17, 18]). In this regard, a multiple-objective sizing procedure to optimise hydrogen systems has already been presented by us in a previous work [18]. The main performance measures of a PMS are to provide load satisfaction and optimal operation of energy system components under a set of technical (hardware) constrains [19]. However, the choice of control set points affects overall reliability, device intermittency (switching on/off), and ultimately system scale as well as cost. In this context, several PMS strategies which use if-else statements have been proposed [20-23]. However, results confirm that adjusting the control set-points significantly affects overall system performance [24-26]. Optimising the controlling set-points [27] or imposing hysteresis bands on their thresholds [26] are methodologies traditionally used to improve the robustness of a PMS. However, the vast majority of research to date considers a PMS which utilises manually preset (rigid) control set-points that do not adapt to real-time variations of renewables, electric load or battery state of charge. Such Power Management Strategies are essentially 'passive' in their response to fluctuations of forcing parameters (e.g. electric load, renewables availability).

To realise a PMS which 'actively' adapts its controlling set-points to operating conditions, techniques such as Particle Swarm Optimisation (PSO) [28-30], Genetic Algorithms (GA) [20] and fuzzy logic [19, 31] have been used. However, such approaches optimise the design of the PMS at the starting state (t = 0), rather than dynamically (and intelligently) by continuously re-aligning its control set-points over every time step (t), so as to lead to a more effective operation of the energy system. In

addition, a few works have also integrated forecasting techniques, such as persistence methods [32, 33], to implement a 'predictive' PMS (P-PMS) by using forecasts of load demand and renewable resources since they are decision variables which affect the operational impact. In addition to the scarcity of such works, it appears these P-PMS's have only been researched in the context of systems using diesel generators (only). Moreover, the effectiveness of integrating more advanced forecasting techniques such as Neural Networks (NNs) do not appear to have been tested within a predictively optimised PMS. The integration of a P-PMS into hydrogen systems, which are renewable powered, also has additional complicating factors because predicting renewables (e.g. wind speed) does not only affect the reliability of meeting external electric load, but additionally influences the ability to use surplus energy to generate hydrogen fuel stocks via electrolysis. As such the integration of a P-PMS into hydrogen fuel cell systems is more complex, compared to stand-alone systems fuelled by conventional diesel generators. As such, there are no reported studies in the published literature into the effectiveness of using both predictive control and intelligent real-time optimisation in the context of stand-alone hydrogen systems.

This paper presents a sizing method which involves an 'intelligent' PMS that initially sizes systems (at t = 0) using GA's but more importantly, then integrates NNs and a third intelligent technique (PSO) to continually predict forcing parameters (wind speed and load demand) to optimise the PMS (in-real time) as well as the operation of supplemental prime movers (fuel cells). The present paper is a continuation of an earlier study by us whereby a lab-scale (desktop) validation for a P-PMS which integrated a single fuel cell, but no electrolysis or wind turbines [34]. However, the objectives of this paper go further by comparing between a reactive PMS (termed R-PMS) and its predictive counterpart (termed P-PMS) as well as studying the effects of real-time fuel cell optimisation when applied in the context of the P-PMS. The role of integrating real-time predictions and fuel cell optimisation into a stand-alone system are also analysed for their operational impact (Cost of Energy \$/kW-hr, CO2 footprint and device cyclability). These strategies are tested when simulating the control of a conceptual off-grid wind/battery/ hydrogen system which integrates (real) load and wind speed profiles. In this regard, the fuel cell (PSO) optimiser will seek to operate the PEM stack in the vicinity of its peak efficiency (resolved through lab testing). The comparative analysis between reactive and predictive PMS's (applied to the same system) will be based on deriving the Cost of Energy (COE, \$/kW-hr), Excess Energy dumped (EE, %) when a full state-of-charge exist for both batteries and hydrogen

canisters (Ah and kg, respectively). The paper will also compare the systems' Life Cycle Emissions (LCE, kg CO₂-eq) when a R-PMS or P-PMS are used. The duty factor of the fuel cell and electrolyser, which expresses the total power generated (or consumed) per total number of start/stop cycles (kW-h/start-stop) under a similar load meeting reliability, will also be considered. This paper is organised as follows: Section 6.3 presents the system architecture and methods used to size and derive life cycle emissions. Section 6.4 describes the employed reactive and predictive PMSs and fuel cell optimiser followed by the results which are presented and discussed in Section 6.5. The conclusions are summarised in Section 6.6.

6.3 SYSTEM ARCHITECTURE, SIZING AND LIFE CYCLE EMISSIONS

The layout of the considered stand-alone wind/battery/hydrogen (WG/BAT/H2) system is shown in Figure 6-1. The main components of the energy system simulated in this study are wind turbines (WG), fuel cells (FC), electrolysers (ELC), hydrogen canisters (H2), batteries (BAT) and Inverter (INV). The system considered serves an external dynamic load of 23,688kW-hr/year whereby power demand is to be primarily satisfied by wind turbines. Due to the intermittent nature of renewably generated power, batteries and fuel cells are used to supplement any deficits during periods of mismatched availability or higher load demand. Batteries are however not used for seasonal storage but rather to cover transient start-up periods of the supplemental prime movers (fuel cells). A dump load is then connected to the DC bus to handle any remaining surplus power if batteries and hydrogen canisters are fully charged. The simulations utilise device capacities, unit costs, operational lifetime, and equivalent CO₂ emissions over the lifetime of the system which have been listed in an earlier work published by us [18]. The following subsections are dedicated to describing the modelling methodology in this paper. For each optimisation run, the system behaviour is simulated over one year period (8,760hours) in order to capture seasonal variations of wind speed which have an impact of the accuracy of NN predictions [35].


Figure 6-1: The hydrogen stand-alone system used to test the effects of the R-PMS, P-PMS and fuel cell optimisation.

6.3.1 Wind turbines

The time resolved power generated by the wind is simulated using the characteristic curve of a commercially available 2kW off-grid wind turbine [36]. Wind data used in the simulations are obtained from the Australian Bureau of Meteorology and measured at a hub height of 10m for the Ocean Reef meteorological station (Western Australia, latitude: -31.75°, longitude: 115.8°). The measured wind speed data has a resolution of one hour [37]. The effect of wind shear, which represents the variation of wind speed with hub height, is also considered by recalibrating each data point of wind speed (measured at a reference height H_0 =10m) to the hub height of the wind turbine in the simulations (H = 18m) using the following equation:

$$v = v_0 (H/H_0)^{\alpha} \tag{6.1}$$

In this regard, v and v_0 are the wind speed at H and H_0 , respectively, whilst α is the roughness coefficient of the earth surface, and taken in this study at 1/7 corresponding to open land [38]. The AC/DC converter shown in Figure 6-1 represents a built-in rectifier and its characteristics are included into the turbine's power curve since it is absorbed in the relationship between wind speed and net output power. The excess (dumped) energy is renewable energy that is converted by primary movers (wind turbines) but not consumed to meet the useful load or diverted to storage devices. The total excess energy produced by the system is the sum of the excess energy at each time step t, and can be expressed as follows [18]:

$$E_{exc} = \sum_{t=0}^{T} P_{exc}(t) \,\Delta t \tag{6.2}$$

In this regard, $P_{exc}(t)$ is the amount of excess power diverted to dump loads over the length of any time interval Δt . The percentage of excess energy, from that originally (renewably) derived, is then calculated as:

 $EE = (E_{exc} / \sum_{t=0}^{T} P_{ren}(t) \Delta t) \times 100$ (%) 6.3

6.3.2 Fuel Cells and Electrolysers

Supplementary power is provided by hydrogen fuel cells in this study which focuses on comparing between a R-PMS and P-PMS. However, the simulations can also be modified and tested with other prime movers. The nominal characteristic curve for a Ballard Nexa 1.2kW Proton Exchange Membrane (PEM) fuel cell stack [39] is used to model each fuel cell in operation. Although it allows an accurate estimation of the hydrogen consumption over the power range defined, the characteristic curve does not include the transient start-up dynamics which are important for a more realistic integration into a dynamically responding stand-alone energy system [34]. The transient start-up characteristics of this Ballard Nexa 1.2kW PEM fuel cell stack have already been experimentally derived and presented by us in an earlier work [18] but are also incorporated into the present study so as to accurately simulate fuel cell behaviour over both the R-PMS and P-PMS.

The hydrogen production rate of an electrolyser \dot{V}_{elc} is given by Faraday's Law [25, 40]:

$$\dot{V}_{elc} = \mu_{elc} \frac{N_c I_{elc}}{C_{H_2}} \,(\text{L/s}) \tag{6.4}$$

In this regard, N_c is the number of cells for the electrolyser, C_{H2} is the conversion coefficient (8,604 Ah⁻¹) [40, 41] and μ_{elc} is a utilisation factor which is taken as 0.7 [40]. Each PEM electrolyser unit is rated at 1kW ($P_{elc,max} = 1kW$) in this research. Equation (6.4) has been extensively used in published research to estimate the hydrogen production rate of electrolysers given their power and conversion efficiencies. However, this model does not include transients such as the start-up time which also ultimately constrain the utilisation of the electrolyser [22]. Therefore, the transient start-up dynamics for the employed electrolyser are also incorporated into simulations within the present study [22]. In this study, the duty factor of the fuel cell (or electrolyser) is calculated as the total power generated (or consumed) per total number of start/stop cycles (kW-h/start-stop) under a similar load reliability.

6.3.3 Energy Storage

Transient Storage: Lead acid batteries are used for short-term transient energy storage in this study and can be represented by the following mathematical model [42]:

$$E_{bat}(t) = E_{bat,0} + \int_0^t V_{bat}(t) I_{bat}(t) dt$$
6.5

In this regard, $E_{bat,0}$ is the assumed battery charge (7.92kW-hr) over the very first time interval (t = 0). Beyond that interval, $V_{bat}(t)$ as well as $I_{bat}(t)$ dictate the battery voltage and current at any time interval t. The percentile Battery State of Charge (B_{SOC}) at each time step (t) is defined according to the following:

$$B_{SOC}(t) = \left(E_{bat}(t)/E_{bat,max}\right) \times 100 \quad (\%)$$
6.6

The state of charge limits are B_{min} =40% and B_{max} =100% whilst $E_{bat,max}$ is the maximum battery storage capacity. Over each time step (Δt), the maximum allowable charging and discharge rate of the battery bank ($P_{B_cCharge}$ and $P_{B_cDischarge}$, respectively) are calculated to determine whether each battery can absorb a fraction of the surplus in the case of charging (or contribute to serving the load in the case of discharging) and given as follows [33, 43]:

$$P_{B_{charge}}(t) = (-kbE_{bat,max} + kE_{1,0}(t)e^{-k\Delta t} + E_{0}(t)kb(1 - e^{-k\Delta t}))/(1 - e^{-k\Delta t} + b(k\Delta t - 1 + e^{-k\Delta t}))$$
6.7

$$P_{B_Discharge}(t) =$$

$$\left(kE_{1,0}(t)e^{-k\Delta t} + E_0(t)kb(1 - e^{-k\Delta t})\right) / \left(1 - e^{-k\Delta t} + b(k\Delta t - 1 + e^{-k\Delta t})\right)$$
6.8

In the above equations, Δt is the time interval (1hour) whilst the capacity ratio b = 0.305 and the rate constant $k = 2.12 h^{-1}$ are technical parameters for the employed lead-acid battery [44]. E_0 is the total energy available in the battery at the beginning of each time interval and $E_{1,0}$ is the amount of energy (kW-hr) above the B_{min} limit. More details about the calculation of maximum charging and discharging rates can be found in [43].

Long-Term Storage: The integrated system under investigation is assumed to store hydrogen in metal hydride canisters. At each time step, the amount of hydrogen in the canisters is given as follows [40]:

$$E_{H2}(t) = E_{H2,0} + \int_0^\tau (\dot{V}_{elc} \Delta H / V_T - \dot{V}_{fc}(t) \Delta H / V_T) dt$$
 6.9

In the above formula, $E_{H2,0}$ is the energy stored in each hydrogen canister (14,190kJ) over the very first time interval (t = 0), \dot{V}_{elc} is the electrolyser hydrogen production rate (L/s), \dot{V}_{fc} is the fuel cell hydrogen consumption rate (L/s), V_T is a conversion constant (22.4 l/mol) and ΔH is hydrogen's enthalpy (286 kJ/mol). The hydrogen canister's percentile state-of-charge (H_{SOC}) at any time step (t) is therefore given as follows:

$$H_{SOC}(t) = (E_{H2}(t)/E_{H2,max}) \times 100$$
 (%) 6.10

In this regard, $E_{H2,max}$ is the maximum capacity of the hydrogen canister (141,900kJ). The minimum and maximum limits are set to H_{min} =10% and H_{max} =100%, respectively.

6.3.4 DC/AC Inverter

An inverter converts electrical power from direct (DC) to alternating form (AC). In this study, the DC/AC inverter at the load side is modelled using its efficiency as follows:

 $P_{out} = P_{in} \,\mu_{in\nu} \tag{6.11}$

In this regard, $\mu_{inv} = 0.95$ is the inverter's conversion efficiency [18] and P_{in} as well as P_{out} are the inverter's input (DC) and output power (AC), respectively.

6.3.5 Sizing

System sizing is formulated as a single objective function designed to optimise (minimise) the Cost of Energy (COE).

$$F(component units, LPSP) = \min(COE)$$
6.12

To solve this, GA's are applied using the MATLAB optimisation toolbox (v.2012b), with settings as follows: four subpopulations with 100 individuals; scattered crossover function with 0.8 crossover fraction; the elite count is 2; rank, constraint dependent function are used for the scaling and mutation and; the number of generations is set to 100. The algorithms seek to identify the number of wind turbine units, fuel cells, electrolysers, batteries, hydrogen canisters and capacity of DC/AC inverter as decision variables. The COE may be expressed as [14]:

$$COE = C_{annual} / E_{annual}$$

$$6.13$$

Here, C_{annual} is the total annual cost (\$) and E_{annual} is the total annual energy (kW-hr) delivered to the useful load (does not include excess load which is dumped). Costs which contribute to C_{annual} include capital costs, replacement costs, operation and maintenance costs, and the discount rate utilised [45]. In this study, a value of 6% discount rate has been used for a project lifetime of 25 years. For the WG/BAT/H2 system, sizing is also subject to the following constraints being satisfied:

$$H_{SOC,end} \ge H_{SOC,initial}$$
 6.14

$$N_{i,min} \le N_i \le N_{i,max} \tag{6.15}$$

In this context, $H_{SOC,initial}$ and $H_{SOC,end}$ are the H_{SOC} at the beginning (t = 0) and end (t = 8,759 hours) of each calendar year, $N_{i,min}$ and $N_{i,max}$ are minimum and maximum allowable number of units from each component, respectively. Although the constraints can be varied, the limits used to guide the optimisation algorithm in this research are shown in Table 6-1.

Baramator	Value,	Parameter	Value,
Farameter	Ref	Farameter	Ref
$B_{SOC}(t=0)$	100%	H _{max}	100%
B _{min}	40%	$N_{WG}[min, max]$	[1,25]
B _{max}	100%	$N_{FC}[min, max]$	[1,25]
f	30%	$N_{ElC}[min, max]$	[1,25]
r	0.2	N _{BAT}	12
$H_{SOC}(0)$	30%	$N_{H2}[min, max]$	[1,25]
H _{min}	10%	N _{INV} [min, max]	[10,20]

Table 6-1: Initial values (at t = 0) for system operational parameters and optimisation constraints

In hybrid energy systems, the reliability of meeting an external load can be expressed by the Loss of Power Supply Probability (LPSP) [10, 46-55]. The LPSP index used in this study is slightly different from the commonly used one and been presented by us in an earlier work [18]. The formulation used in our studies takes into account load losses during transient start-up time of supplementary prime movers (PEM fuel cell) which is usually ignored in the commonly applied definition for LPSP [10, 46-55]. This is important to consider particularly if a predictive PMS which also integrates device startp transients is being employed. An intelligently optimised PMS should consider such transients if determining device switching and integrated with time resolved predictions of wind speed and load demand.

$$LPSP = LPSP_{common} + \left(\sum_{t=1}^{T} LPS_{FC_transient}(t,i) / \sum_{t=1}^{T} P_{Load}(t) \Delta t\right)$$
6.16

$$LPSP_{common} = \sum_{t=1}^{T} LPS(t) \Delta t / \sum_{t=1}^{T} P_{Load}(t) \Delta t$$
6.17

In the above equations, $LPS_{FC_transient}$ is the loss of power supply during fuel cell transient start-up, LPS (kW) is the loss of power during low generation periods and P_{Load} (kW) is the load demand. The term $LPSP_{common}$ represents the commonly used LPSP equation [46] and (Δt) is the simulation time interval (1hour).

The fuel cell transient start-up time (τ) is estimated using the following experimentally derived formula where, i_{FC} is the fuel cell current [18]:

$$\tau = 1.7e^{-6}i_{FC}^5 - 3.4e^{-4}i_{FC}^4 + 2.4e^{-2}i_{FC}^3 - 0.79i_{FC}^2 + 11i_{FC} - 1.1$$
6.18

To estimate the load losses due to transient start-ups, which vary based on load and may span up to two minutes for the fuel cell used in this study [18], the hourly averaged fuel cell's response is divided into one-minute resolved time slots and the output power over the transient time is summed up and considered as a loss. The same approach is used to incorporate the electrolyser start-up transients, which spans four minutes [22], though they have no direct impact on the LPSP calculations but affect the amount of hydrogen produced. It should be noted here that wind power and load demand are assumed constant during each simulation interval (1hour). In order to consider the LPSP, the following constraint is also considered during the optimisation process:

$$LPSP \leq LPSP_{max}$$

Where, $LPSP_{max}$ is the maximum allowable LPSP. Two values are used for the LPSP, 0.05 and 0.0015 which corresponds to an annual loss of 1,184kW-hr and 35kW-hr, respectively, from the total annual demand (23,688 kW-hr)

6.19

6.3.6 Life Cycle Emissions

Life cycle (cradle-to-grave) emissions generated during the manufacturing, transportation, operation and decommissioning of the system are calculated relative to amount of energy converted (or stored) by each system component [14]. Estimating greenhouse gas emissions (normalised by energy units converted) is preferable because some components are used for most of the year, such as wind turbines, whereas others are used less frequently such as fuel cells and electrolysers [14]. Data for equivalent CO₂ emissions attributed to each system component is retrieved from the literature [14, 18]. The annual life cycle emissions are calculated from the sum of the emissions by the system components using the following expression:

$$LCE = \sum_{i=1}^{N} \beta_i * E_i \tag{6.20}$$

Where, β_i (kg CO₂-eq/kW-hr) is the equivalent CO₂ emissions of a component and E_i (KW-hr) is the amount of energy converted by (or drawn from) each component.

6.4 POWER MANAGEMENT STRATEGIES

In this paper, a single PMS for controlling component switching is tested, but under both reactive and predictive modes of operation. The main objective of any PMS is the satisfaction of load requirements while maintaining operation of system components within an acceptable range of technical constraints. So, to provide a valid basis of comparison, the baseline architecture of the two PMSs tested are the same in this study. The difference between the two however lies in the use of NNs to predict important governing variables (wind speed, load demand) in the P-PMS. Both versions of the PMS (reactive and predictive) are tested using hourly resolved wind speed and load demand data. A general overview of the logic behind either PMS is given in Figure 6-2. Whether under a R-PMS or P-PMS, the algorithm update its status by reading the input data at a single time interval (t)(wind speed and load demand) so as to calculate the net power over that time step (t) as the difference between the renewably generated power, P_{ren} , and load demand, P_{Load} :

$$P_e(t) = P_{ren}(t) - P_{Load}(t)$$

$$6.21$$

The next step for the algorithm is to decide if any net excess power exists ($P_e(t) \ge 0$). If so, these surpluses are handled through the 'battery charging and electrolysis' mode of operation (Figure 6-2a), with the logic of the 'battery charging and electrolysis' mode explained in the Appendix 6.8. If the renewably generated power is less than the load demand, $P_e(t) < 0$, one of three operation modes can be used to satisfy the load. Although the general architecture of all three modes (Figure 6-2- blocks b, c, or d) remains the same, if NN's are used to predict (one time step ahead), this infers a P-PMS is used. Without the NN's, the algorithm reverts to a R-PMS. Both are explained later. The first mode under both R-PMS or P-PMS is the Wind/Hydrogen mode (Figure 6-2b) which uses the hydrogen system for supplying the whole power deficit. The second is the Wind/Battery mode (Figure 6-2d) where only the battery recompenses the power deficit. The third is a Wind/Battery/Hydrogen mode (Figure 6-2c) where the deficit is shared by the battery and fuel cell. The decision as to which operation mode is used to provide the baseline (wind) and supplemental power to satisfy the load demand is determined via a switching algorithm (R-PMS or P-PMS). It is this switching algorithm which is the focus of the present study and which features two scenarios. The first is a reactive algorithm whereas the second is a predictive algorithm. When the reactive algorithm is used the PMS is termed R-PMS whereas P-PMS is a term used to refer to the PMS when the predictive switching algorithm is employed.

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6.4.1 Reactive PMS (R-PMS)

The logic of the reactive switching algorithm is shown in Figure 6-3. If $B_{SOC}(t) > (B_{min} + f)$ and the maximum power can be drawn from the battery $(P_{B_{a}Discharge})$ is at least a certain percent (r) more than the requested power $P_{e}(t)$, then the whole deficit is supplied by the battery. The parameter (r) represents a threshold which is used to account for the fact that renewables can fluctuate during the time in which the load is being met and a safety margin (r) is advantageous so as to limit excessive switching ON/OFF. On the other hand, (f) is a (B_{SOC}) margin (above B_{min}) beyond which the battery is considered more likely to serve the load over the current time step. In case $P_{B_{a}Discharge}(t) < (1 + r)|P_{e}(t)|$, the battery is considered able to only supply part of the requested power and therefore the Wind/Battery/Hydrogen mode is activated in order to allow the battery and the fuel cell to share the supplementary load. The

Wind/Battery/Hydrogen mode is also activated if the battery charge lies between $B_{SOC}(t) \ge B_{min}$ and $B_{SOC}(t) \le B_{min} + f$. In the Wind/Battery/ Hydrogen mode and if the fuel cell optimiser is not engaged, the deficit is met by operating the fuel cell at its maximum capacity and any additional shortage augmented by battery storage unless the battery is considered fully discharged $B_{SOC}(t) < B_{min}$.



Figure 6-3: Reactive switching algorithm.

6.4.2 Predictive PMS (P-PMS)

The predictive switching algorithm is shown in Figure 6-4. This algorithm is similar to its reactive counterpart except that decisions as to which operation mode should apply to supplement the power deficit are taken one step earlier. In this case, deficits are forecast through predictions of both the wind speed (m/s) and load demand (kW). The merits of a predictive PMS are believed to allow the early activation of energy system components with slow transient responses, thereby no loads are missed during the transient period. Testing the effectiveness of the P-PMS thus requires the simulations integrate device start-up (transient) characteristics. In this switching algorithm, the expected renewable power (\hat{P}_{ren}) and load demand (\hat{P}_{Load}) at the next time step (t + 1) are forecasted and the system's expected net power, $\hat{P}_e(t + 1)$, is calculated as follows:

$$\hat{P}_{e}(t+1) = \hat{P}_{ren}(t+1) - \hat{P}_{Load}(t+1)$$
6.22

The system's expected net power ($\hat{P}_e(t + 1)$) is used to estimate the battery state of charge at the next time step, $B_{SOC}(t + 1)$ which is then used to assign an operation mode for supplementing the generation deficit during the next time interval (Figure 6-2blocks b, c or d). In the predictive switching algorithm, the spinning reserve factor (r) plays slightly different role since it accommodates the short-term renewables fluctuations as well as forecasting errors. Besides testing the passive power sharing, the Wind/Battery/Hydrogen mode is tested when the power deficit is actively distributed between the fuel cell and battery storage via real-time optimisation process with the objective to maximise the fuel cell efficiency whenever it is possible.



Figure 6-4: Predictive switching algorithm.

Compared to other NNs, the Radial Basis Function NN (RBF-NN) is proven to have better approximation ability for highly dynamic and nonlinear applications [35, 56]. Therefore, RBF-NNs are used to perform the forecasting of wind speed and load demand. The training and prediction accuracy for the RBF-NN when applied for one hour ahead wind speed forecasting has been already studied by us in a previous research [35] when hourly resolved wind speed data along with solar irradiance data (belongs for the same location) applied Length of Training Pattern (LTP) spanning 10hours (which is also used in this study). For the short-term load demand forecasting, the same training methodology has been used where only hourly resolved load demand data are used for training (no solar irradiance data are used). The accuracy of wind speed and load demand forecasting is expressed as the Absolute Percentage Error (APE) and Mean APE (MAPE) which are calculated as follows:

$$APE = |(y(t) - \hat{y}(t))/y(t)| \times 100\%$$
6.23

$$MAPE = (1/T)\sum_{i=1}^{T} APE$$

$$6.24$$

In the above equation, y(t) is the measured wind speed (or load demands) over a time step (*t*) and $\hat{y}(t)$ is the predicated wind speed or load demand over the same time step. The prediction errors derived during the training (Stage 1, Figure 6-4) for both to wind speed and load demand are shown in Figure 6-5. The operational profiles for the actual and predicted B_{SOC} for the same time period (two weeks) are also shown in Figure 6-5. From this figure, it can be seen that the prediction error of the employed RBF-NN is very small and the estimated B_{SOC} closely follows the actual one. The initial values of the controlling parameters for the tested PMSs as well as the values for optimisation constraints are listed in Table 6-1.



Figure 6-5: Operational profiles for the NN which is integrated into P-PMS over two weeks starting 1st Jan. The prediction accuracy of the load demand (solid red) and wind speed (dashed blue) are shown. The actual and predicted profile for the battery state of charge is also shown.

6.4.3 Fuel cell efficiency optimiser

To examine the effects of using PSO to optimise fuel cell efficiency, the P-PMS also operates with (and without) the fuel cell optimiser. To seek the optimal power setting, PSO considers the following local optimisation problem which is solved at the beginning of each time interval (t) and for a duration Δt [57]:

$Maximise J(t) = P_{net}(t)\Delta t / (P_{fc}(t) / \mu_{fc}(t) + P_{bat}(t) / \mu_{bat})$	6.25
The real-time optimisation problem is subject to the following constraint:	
$0 \le P_{fc}(t) \le P_{fc,max}$	6.26

$$0 \le P_{bat}(t) \le P_{B_{Discharge}}$$

$$6.27$$

$$B_{min} \le B_{SOC}(t) \le B_{max} \tag{6.28}$$

$$P_{net}(t) = P_{bat}(t) + P_{fc}(t)$$

$$6.29$$

Where, $\mu_{bat} = 0.95$ is the battery bank conversion efficiency and μ_{fc} is the fuel cell efficiency which dynamically varies as a function of the generated power and is shown in Figure 6-6.





Fuel cell efficiency may be derived by measuring the output voltage and hydrogen consumption rates at loads (currents) over the fuel cell dynamic range (2A and 50A). Figure 6-6 shows the measured efficiency characteristics. When the fuel cell efficiency optimiser is activated alongside the P-PMS, the real-time optimisation problem is solved by PSO at the beginning of each time step in order to determine the optimal power sharing between the battery bank and fuel cells (when the battery/hydrogen mode is selected). The main objective is to operate the fuel cell at its maximum

efficiency whenever possible. Since the described real-time optimisation problem needs to be solved at the beginning of each time interval, the speed at which the employed search tool reaches an optimal solution is very important. Compared to many other well-known optimisation techniques, PSO is proven to be more efficient and faster for finding optimal solutions especially for problems that involve three or less optimisation variables [28, 58]. Hence, PSO solves the real-time optimisation problem shown by equation (6.13) where the optimisation variables are fuel cell power, $P_{fc}(t)$, and battery discharge power, $P_{BDis}(t)$. The PSO's cognitive (c_1) and social (c_2) parameters are both set to 1.5, and the maximum number of iterations is set to 50 [28].

6.5 RESULTS AND DISCUSSION

6.5.1 Cost of Energy

Table 6-2 summarises the sizing results when a reactive PMS (R-PMS) verses a predictive PMS (P-PMS) is applied to control the operation of the stand-alone WG/BAT/H2 system. The optimum numbers of components and the corresponding COE have been derived when targeting two levels of load meeting reliability: LPSP=0.05 and 0.0015. The data presented in Table 6-2 also shows the effects of considering device start-up transients (fuel cell, electrolyser) verses scenarios when only nominal (steady-state) characterises are used. All the simulations are undertaken for a fixed battery capacity (12 units) so as to restrict batteries to only meeting transients, and not long-term energy shortage.

These results show that ignoring the transient start-up time of the prime back-up affects system sizing, especially if the targeted reliability (LPSP) is relatively high (0.0015). The COE for the system sized with the transients of the fuel cell included, is 23% higher than without including the fuel cell transients. The cost increment is mainly because a greater capacity (i.e. number of units) for prime movers are need when transients are considered. The sizing of systems which used only steady-state device characteristics obviously assumes no load loss during the start-ups. As such, when transients are included, the capacity of other prime movers (primarily wind turbines) needs to increase so as to bridge the gap during fuel cell start-ups. This highlights the importance of considering transient start-up time of back-up components which is unfortunately overlooked by the majority published sizing studies [11, 46, 59].

PMS	LPSP _{max}		WG (Unit)	FC (Unit)	ELC (Unit)	BAT (Unit)	H2 (Unit)	INV (kW)	COE (\$/kW- hr)
	With device	0.05	10	3	6	12	16	12	1.13
R-PMS	transients	0.0015	14	13	5	12	20	18	2.35
	Without device transients	0.0015	11	9	8	12	22	18	1.86
	With device	0.05	10	4	6	12	19	14	1.27
P-PMS	transients	0.0015	12	9	7	12	21	18	1.88
P-PMS	With	0.05	10	4	6	12	14	12	1.23
(+ FC optimiser)	device transients	0.0015	11	11	8	12	20	18	2.06

Table 6-2: Summary of optimal solutions by the R-PMS, P-PMS and P-PMS (+ FC optimiser) for a NN (wind speed) prediction accuracy of MAPE=0.528%.

For sizing methods which do integrate device transients, another observation is that a stand-alone hybrid energy system controlled by P-PMS has a cost advantage over that controlled by R-PMS, but only if the sizing method targets high reliability. For a lower load meeting reliability target ($LPSP_{max} = 0.05$), the predictive PMS results in a COE of 1.27\$/kW-h which is slightly higher than that for the R-PMS (1.13\$/kW-h). On the other hand, when a higher reliability target is set ($LPSP_{max} = 0.0015$) for the sizing algorithm, the P-PMS results in 1.88\$/kW-h COE which is 22% lower compared to that resulted from the R-PMS (2.35\$/kW-h). These cost savings mainly come from the predictions which reduce the number of wind turbines are by 2 units (15%) and fuel cells by 4 units (36%). These results further highlight that including predictive PMS's into hydrogen systems can lead to appreciable reductions in the cost of energy, compared to only running those systems with reactive PMS's.

The third observation is that the superiority of P-PMS strongly depends on the accuracy of the tool employed to perform the renewables and load demand predictions. Table 6-3 shows the optimal solutions achieved when NNs with two different wind speed prediction accuracies (MAPE= 0.528% and 0.213%) are used for the P-PMS.

For both listed solutions, the load demand prediction accuracy is MAPE=1.528%. From this table it can be observed that a significant increase in the system COE (more than 67%) has occurred because of using NN with 0.3% more prediction error. This indicates that P-PMS is extremely sensitive to the performance of the forecasting tool.

Table 6-3: The effect of wind speed prediction error on the optimal sizing ofWG/BAT/H2 controlled by P-PMS; load prediction error MAPE = 1.528% andLPSP_{max} = 0.0015

Wind speed prediction error MAPE (%)	WT (Unit)	FC (Unit)	ELC (Unit)	BAT (Unit)	H2 (kg)	INV (kW)	COE (\$/kW-hr)
0.528	12	9	7	12	21	18	1.88
0.213	20	18	22	12	17	18	3.79

To show the effects of applying the PSO real-time optimisation of the fuel cell, the power density distribution, which is calculated as the percentage of power delivered by the fuel cell at each power level (0.1kW, 0.2kW,...., 1.2kW) to the total power delivered over one year, in relation to the fuel cell efficiency with and without the real-time fuel cell efficiency optimiser is shown in Figure 6-6. From this figure it can be seen that when the real-time optimisation algorithm is applied, the output power density of the fuel cell (green bars) 0.3kW and 0.46kW, which correspond to the highest efficiency, are increased by 7% and 11%, respectively, compared to the case when no real-time optimisation is applied (red bars). In the other hand, the power density at the other power levels is reduced. This shows the applied PSO real-time fuel cell efficiency optimiser operates of the fuel cell unit more often when it is closer to its peak efficiency. AS such, applying a fuel cell efficiency optimiser positively impacts system sizing. Results also show that systems sized with the fuel cell optimiser activated have 13% less COE, when high load meeting reliability targets are considered (LPSP_{max} = 0.0015), compared to the case where the optimiser is not activated.

6.5.2 Life Cycle Emissions, Excess Energy and Device Intermittency

Further investigations are undertaken into the impact of PMSs on the percentage of Excess Energy (EE; %), Life Cycle Emissions (LCE; kg CO2-eq) as well as duty factor (kW/start-stop) for the fuel cell and electrolyser units and are listed in Table 6-4.

Operation parameter	R-PMS	P-PMS	P-PMS (+ FC optimiser
Excess Energy (%)	55.56	46.25	44.02
CO ₂ LCE (kg CO ₂ -eq/year)	1,296	1,189	1,133
FC duty factor (kW/start-stop)	0.68	0.98	0.69
FC Start/Stop (cycles/year)	597	630	649
ELC duty factor (kW/start-stop)	6.28	4.9	4.58
ELC start/stop (cycles/year)	610	609	505

Table 6-4: Annual operational characteristics when R-PMS, P-PMS and P-PMS (+ FCoptimiser) are applied for the hydrogen system. $LPSP_{max} = 0.0015$

Data reveals that systems controlled by a predictive PMS results in less excess (dumped) energy and environmental footprint compared to that controlled by a reactive PMS. When the R-PMS is used for the WG/BAT/H2 system, 55.56% of the renewably generated power is diverted to a dump load which is around 9% and 11% higher than that for systems controlled by P-PMS and P-PMS (+ FC optimiser), respectively. Power generated by wind turbines but dumped is undesirable because although it helps achieve high load meeting reliability during some periods, it leads to excessive costs. Regarding the environmental footprint, around a 8% and 13% reduction in the LCE is achieved when P-PMS and P-PMS (+ FC optimiser) are used, respectively. A further comparison of the duty factor for the fuel cell shows that a hybrid system controlled by P-PMS or P-PMS (+FC optimiser) acquires higher fuel cell duty factor (0.98kW/startstop and 0.69kW/start-stop, respectively) compared to that for R-PMS (0.68kW/startstop). In contrast, the system controlled by R-PMS possesses a higher electrolyser duty cycle (6.28kW/start-stop) compared to that for P-PMS (4.9kW/start-stop) and OP-PMS (4.58kW/start-stop). Regarding the start-stop cycles, results show that a hydrogen system controlled by predictive strategies relies more on the long-term back-up units (fuel cells) to satisfy the load requirements. The annual rate of start-stop cycles of the fuel cell has increased 5% and 8% when P-PMS and P-PMS (+ FC optimiser), respectively, are used for controlling the system. Excessive intermittency of fuel cell units can cause a performance degradation [26]. For R-PMS, the start-stop cycles rate (597 cycles/year) would sum up to 2,985 cycles over the fuel cell's lifetime (5 years). However, a recent study has shown that a PEM fuel cells can undergo up to 1,562 start/stop cycles without a significant performance degradation if a proper start/stop

procedure is followed [60]. This highlights the importance of considering the start-stop cycles of commercially available hydrogen technologies into the sizing methodologies of stand-alone energy systems.

Finally, results have shown that an optimised predictive strategy P-PMS (+ FC optimiser) outperforms the non-optimised one (P-PMS) in terms of renewables penetration and environmental footprint. The hydrogen system controlled by the P-PMS (+ FC optimiser) generates 44.02% excess energy and 1,133kg CO2-eq greenhouse emissions which are both lower than for the P-PMS. This is however at the expense of the overall cost of energy (COE) where the COE for the system controlled by P-PMS (+ FC optimiser) is around 9% higher than for the system controlled by the P-PMS. This comes mainly from increasing the number of fuel cells which may be because the employed real-time optimisation algorithm forces the fuel cell to operate at its higher efficiency which occurs at low power levels (around 0.3kW). This limits the contribution of each fuel cell to the total load demand which means more units are required to satisfy greater demand levels.

6.6 CONCLUSIONS

In this paper, the application of NN-based (predictive) PMS in the context of sizing stand-alone hydrogen systems has been tested and analysed. The predictive PMS uses real-time NN predictions of renewable resources (wind speed) and load demand for controlling the switching of the system components, and PSO real-time optimisation of the fuel cell operation. Genetic Algorithm (GA) is used for the components sizing and the reliability of the archived optimal solutions is assessed using a modified LPSP index which has been presented by the authors is a previous work. The effects of some parameters such as the transient start-up time of the fuel cells, NN accuracy, LPSP level and fuel cell optimisation are investigated. In addition, the performance of the predictive PMS has been compared to rule-based (reactive) PMS based on the Cost of Energy (COE, \$/kW-hr), Excess Energy (EE, %), Life Cycle Emissions (LCE, kg CO2-eq) as well as the duty factor (kW/start-stop) of the hydrogen components. The main outcome of this study may be summarised as follows:

 Ignoring the transient response of the fuel cell and electrolyser considerably impacts the optimal solutions achieved when sizing stand-alone hydrogen systems. This impact appears more pronounced if the desired load meeting reliability (LPSP) is higher.

- Using a predictive PMS to control the operation of a stand-alone hydrogen system results in an operational impact which can be more cost-effective, efficient and environmentally friendly, compared to a reactive PMS. However, these improvements are attained only if the GA used for sizing targets a higher reliability level and device transient dynamics are incorporated.
- Because the highest efficiency of the fuel cell occurs at low power levels, a stand-alone hydrogen system controlled by predictive power management strategy which is additionally optimised for fuel cell efficiency, has no cost advantage compared to a PMS that features no fuel cell efficiency optimisation. More work is however warranted in this area.
- The performance of predictive PMS extremely depends on the accuracy (MAPE) of the NN predictions of renewables (wind speed).

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6.8 Appendix

6.8.1 Mode – Battery Charging and Electrolysis

If the batteries are not fully charged, $B_{SOC}(t) < B_{max}$, net excess power is used to increase B_{SOC} . If the surplus is more than the absorption capacity of the battery $P_e(t) > P_{B_Charge}(t)$, excess power is then diverted to the dump load, $P_{Dump}(t)$. In case the battery storage is fully charged ($B_{SOC}(t) = B_{max}$) but the hydrogen canisters are not fully charged ($H_{SOC}(t) < H_{max}$), the surplus is used to operate the electrolysers for hydrogen production if $P_e(t)$ is less than or equal to the electrolysers rating. If the electrolysers cannot handle the whole surplus, $P_e(t) > P_{Elec}$, then the electrolyser is operated at its maximum capacity for hydrogen production and the excess is diverted to the dump load. In case both the battery storage and hydrogen canisters are fully charged, then the whole surplus is diverted to the dump load.



Figure 6-7: Algorithm for 'battery charging and electrolysis' mode.

6.8.2 Mode – Battery Charging and Electrolysis

6.9 **REFERENCES**

- [1] O. Erdinc, O. Elma, M. Uzunoglu, and U. S. Selamogullari, "Real-time performance analysis of an optimally sized hybrid renewable energy conversion unit," *Energy and Buildings*, vol. 75, pp. 419-429, 2014.
- [2] F. Baghdadi, K. Mohammedi, S. Diaf, and O. Behar, "Feasibility study and energy conversion analysis of stand-alone hybrid renewable energy system," *Energy Conversion and Management*, vol. 105, pp. 471-479, 2015.
- [3] D. P. Clarke, Y. M. Al-Abdeli, and G. Kothapalli, "The effects of including intricacies in the modelling of a small-scale solar-PV reverse osmosis desalination system," *Desalination*, vol. 311, pp. 127-136, 2013.
- [4] K. Y. Lau, M. Yousof, S. Arshad, M. Anwari, and A. Yatim, "Performance analysis of hybrid photovoltaic/diesel energy system under Malaysian conditions," *Energy*, vol. 35, pp. 3245-3255, 2010.

- [5] M. C. McManus, "Environmental consequences of the use of batteries in low carbon systems: The impact of battery production," *Applied Energy*, vol. 93, pp. 288-295, 2012.
- [6] O. Erdinc and M. Uzunoglu, "The importance of detailed data utilization on the performance evaluation of a grid-independent hybrid renewable energy system," *International Journal of Hydrogen Energy*, vol. 36, pp. 12664-12677, 2011.
- [7] A. Chauhan and R. P. Saini, "A review on Integrated Renewable Energy System based power generation for stand-alone applications: Configurations, storage options, sizing methodologies and control," *Renewable and Sustainable Energy Reviews*, vol. 38, pp. 99-120, 2014.
- [8] O. Ekren and B. Y. Ekren, "Size optimization of a PV/wind hybrid energy conversion system with battery storage using simulated annealing," *Applied Energy*, vol. 87, pp. 592-598, 2010.
- [9] M. Lalwani, D. Kothari, and M. Singh, "Size optimization of stand-alone photovoltaic system under local weather conditions in India," *International Journal of Applied Engineering Research*, vol. 1, pp. 951-961, 2011.
- [10] A. Maleki and A. Askarzadeh, "Artificial bee swarm optimization for optimum sizing of a stand-alone PV/WT/FC hybrid system considering LPSP concept," *Solar Energy*, vol. 107, pp. 227-235, 2014.
- [11] A. Maleki and A. Askarzadeh, "Comparative study of artificial intelligence techniques for sizing of a hydrogen-based stand-alone photovoltaic/wind hybrid system," *International Journal of Hydrogen Energy*, vol. 39, pp. 9973-9984, 2014.
- [12] R. Jallouli and L. Krichen, "Sizing, techno-economic and generation management analysis of a stand alone photovoltaic power unit including storage devices," *Energy*, vol. 40, pp. 196-209, 2012.
- [13] G. Rohani and M. Nour, "Techno-economical analysis of stand-alone hybrid renewable power system for Ras Musherib in United Arab Emirates," *Energy*, vol. 64, pp. 828-841, 2014.
- [14] Y. Katsigiannis, P. Georgilakis, and E. Karapidakis, "Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables," *IET Renewable Power Generation,* vol. 4, pp. 404-419, 2010.

- [15] X. Zhang, S.-C. Tan, G. Li, J. Li, and Z. Feng, "Components sizing of hybrid energy systems via the optimization of power dispatch simulations," *Energy*, vol. 52, pp. 165-172, 2013.
- [16] R. Dufo-Lopez and J. L. Bernal-Agustin, "Multi-objective design of PV-winddiesel-hydrogen-battery systems," *Renewable Energy*, vol. 33, pp. 2559-2572, 2008.
- [17] J. A. Razak, K. Sopian, Y. Ali, M. A. Alghoul, A. Zaharim, and I. Ahmad,
 "Optimization of PV-wind-hydro-diesel hybrid system by minimizing excess capacity," *European Journal of Scientific Research*, vol. 25, pp. 663-671, 2009.
- [18] A. Brka, Y. M. Al-Abdeli, and G. Kothapalli, "The interplay between renewables penetration, costing and emissions in the sizing of stand-alone hydrogen systems," *International Journal of Hydrogen Energy*, vol. 40, pp. 125-135, 2015.
- [19] A. Hajizadeh and M. A. Golkar, "Intelligent power management strategy of hybrid distributed generation system," *International Journal of Electrical Power* & Energy Systems, vol. 29, pp. 783-795, 2007.
- [20] R. Dufo-Lopez, J. L. Bernal-Agustín, and J. Contreras, "Optimization of control strategies for stand-alone renewable energy systems with hydrogen storage," *Renewable Energy*, vol. 32, pp. 1102-1126, 2007.
- [21] A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M. Fadali, and Y. Baghzouz,
 "Genetic-algorithm-based optimization approach for energy management,"
 IEEE Transactions on Energy Conversion, vol. 28, pp. 162-170, 2013.
- [22] D. P. Clarke, Y. M. Al-Abdeli, and G. Kothapalli, "The impact of renewable energy intermittency on the operational characteristics of a stand-alone hydrogen generation system with on-site water production," *International Journal of Hydrogen Energy*, vol. 38, pp. 12253-12265, 2013.
- [23] D. Giaouris, A. I. Papadopoulos, C. Ziogou, D. Ipsakis, S. Voutetakis, S. Papadopoulou, P. Seferlis, F. Stergiopoulos, and C. Elmasides, "Performance investigation of a hybrid renewable power generation and storage system using systemic power management models," *Energy*, vol. 61, pp. 621-635, 2013.
- [24] E. Dursun and O. Kilic, "Comparative evaluation of different power management strategies of a stand-alone PV/Wind/PEMFC hybrid power system," *International Journal of Electrical Power & Energy Systems*, vol. 34, pp. 81-89, 2012.
- [25] D. Ipsakis, S. Voutetakis, P. Seferlis, F. Stergiopoulos, and C. Elmasides,"Power management strategies for a stand-alone power system using

renewable energy sources and hydrogen storage," *International Journal of Hydrogen Energy*, vol. 34, pp. 7081-7095, 2009.

- [26] D. Ipsakis, S. Voutetakis, P. Seferlis, F. Stergiopoulos, S. Papadopoulou, and C. Elmasides, "The effect of the hysteresis band on power management strategies in a stand-alone power system," *Energy*, vol. 33, pp. 1537-1550, 2008.
- [27] D. P. Clarke, Y. M. Al-Abdeli, and G. Kothapalli, "The impact of using Particle Swarm Optimisation on the operational characteristics of a stand-alone hydrogen system with on-site water production," *International Journal of Hydrogen Energy*, vol. 39, pp. 15307-15319, 2014.
- [28] S. A. Pourmousavi, M. H. Nehrir, C. M. Colson, and W. Caisheng, "Real-time energy management of a stand-alone hybrid wind-microturbine energy system using particle swarm optimization," *IEEE Transactions on Sustainable Energy*, vol. 1, pp. 193-201, 2010.
- [29] S. A. P. Kani, H. Nehrir, C. Colson, and W. Caisheng, "Real-time energy management of a stand-alone hybrid wind-microturbine energy system using particle swarm optimization," presented at the IEEE Power and Energy Society General Meeting, San Diego, CA, 2011.
- [30] D. P. Clarke, Y. M. Al-Abdeli, and G. Kothapalli, "Multi-objective optimisation of renewable hybrid energy systems with desalination," *Energy*, vol. 88, pp. 457-468, 2015.
- [31] S. Zerkaoui, A. Hajjaji, and J. Bosche, "On-line control strategy for instantaneous power management of hybrid power system based on dynamic fuzzy logic controller," in 7th IEEE Conference on Industrial Electronics and Applications, Singapore, 2012, pp. 1130-1136.
- [32] S. Yamamoto, K. Sumi, E. Nishikawa, and T. Hashimoto, "An operating method using prediction of photovoltaic power for a photovoltaic–diesel hybrid power generation system," *Electrical Engineering in Japan,* vol. 151, pp. 8-18, 2005.
- [33] E. I. Vrettos and S. A. Papathanassiou, "Operating policy and optimal sizing of a high penetration RES-BESS system for small isolated grids," *IEEE Transactions on Energy Conversion*, vol. 26, pp. 744-756, 2011.
- [34] A. Brka, G. Kothapalli, and Y. M. Al-Abdeli, "Predictive Power Management Strategies for Stand-alone Hydrogen Systems: Lab-scale Validation," *International Journal of Hydrogen Energy*, vol. 40, pp. 9907-9916, 2015.

- [35] A. Brka, Y. M. Al-Abdeli, and G. Kothapalli, "Influence of neural network training parameters on short-term wind forecasting," *International Journal of Sustainable Energy*, pp. 1-17, 2014. DOI: 10.1080/14786451.2013.873437.
- [36] Anhui Hummer Dynamo Co. Ltd. (access date: 2014, December 8). *Hummer*. Available: <u>http://www.china-windturbine.com/product/2000w.html</u>
- [37] BOM. (access date: 2011, July 20). *Western Australia weather and warnings*. Available: <u>http://reg.bom.gov.au/wa/</u>
- [38] B. S. Borowy and Z. M. Salameh, "Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system," *IEEE Transactions on Energy Conversion*, vol. 11, pp. 367-375, 1996.
- [39] Ballard Power Systems. (access date: 2014, January 10). Nexa power module user's manual man5100078. Available: http://my.fit.edu/~swood/Fuel%20Cell%20Manual.pdf
- [40] A. Bilodeau and K. Agbossou, "Control analysis of renewable energy system with hydrogen storage for residential applications," *Journal of Power Sources*, vol. 162, pp. 757-764, 2006.
- [41] S. Kelouwani, K. Agbossou, and R. Chahine, "Model for energy conversion in renewable energy system with hydrogen storage," *Journal of Power Sources*, vol. 140, pp. 392-399, 2005.
- [42] S. Pedrazzi, G. Zini, and P. Tartarini, "Complete modeling and software implementation of a virtual solar hydrogen hybrid system," *Energy Conversion and Management*, vol. 51, pp. 122-129, 2010.
- [43] J. F. Manwell and J. G. McGowan, "Lead acid battery storage model for hybrid energy systems," *Solar Energy*, vol. 50, pp. 399-405, 1993.
- [44] Power-Sonic Corp. (access date: 2015, January 18). Sealed lead-acid battries technical manual. Available: <u>http://www.power-</u> <u>sonic.com/images/powersonic/technical/1277751263_20100627-TechManual-Lo.pdf</u>
- [45] HOMER Pro, Ver. 1.58,, "National Renewable Energy Laboratory, Golden CO,," 2002.
- [46] A. Kashefi Kaviani, G. Riahy, and S. Kouhsari, "Optimal design of a reliable hydrogen-based stand-alone wind/PV generating system, considering component outages," *Renewable Energy*, vol. 34, pp. 2380-2390, 2009.
- [47] Z. Iverson, A. Achuthan, P. Marzocca, and D. Aidun, "Optimal design of hybrid renewable energy systems (HRES) using hydrogen storage technology for data center applications," *Renewable Energy*, vol. 52, pp. 79-87, 2013.

- [48] H. Yang, W. Zhou, L. Lu, and Z. Fang, "Optimal sizing method for stand-alone hybrid solar-wind system with LPSP technology by using genetic algorithm," *Solar Energy*, vol. 82, pp. 354-367, 2008.
- [49] Y. Bakelli, A. H. Arab, and B. Azoui, "Optimal sizing of photovoltaic pumping system with water tank storage using LPSP concept," *Solar Energy*, vol. 85, pp. 288-294, 2011.
- [50] R. Rajkumar, V. Ramachandaramurthy, B. Yong, and D. Chia, "Technoeconomical optimization of hybrid pv/wind/battery system using Neuro-Fuzzy," *Energy*, vol. 36, pp. 5148-5153, 2011.
- [51] W. Wu, V. I. Christiana, S.-A. Chen, and J.-J. Hwang, "Design and technoeconomic optimization of a stand-alone PV (photovoltaic)/FC (fuel cell)/battery hybrid power system connected to a wastewater-to-hydrogen processor," *Energy*, 2015.
- [52] J. Li, A. M. Gee, M. Zhang, and W. Yuan, "Analysis of battery lifetime extension in a SMES-battery hybrid energy storage system using a novel battery lifetime model," *Energy*, 2015.
- [53] F. Caballero, E. Sauma, and F. Yanine, "Business optimal design of a gridconnected hybrid PV (photovoltaic)-wind energy system without energy storage for an Easter Island's block," *Energy*, vol. 61, pp. 248-261, 2013.
- [54] A. Kaabeche, M. Belhamel, and R. Ibtiouen, "Sizing optimization of gridindependent hybrid photovoltaic/wind power generation system," *Energy*, vol. 36, pp. 1214-1222, 2011.
- [55] B. O. Bilal, V. Sambou, P. Ndiaye, C. Kébé, and M. Ndongo, "Optimal design of a hybrid solar–wind-battery system using the minimization of the annualized cost system and the minimization of the loss of power supply probability (LPSP)," *Renewable Energy*, vol. 35, pp. 2388-2390, 2010.
- [56] S. Yu, K. Wang, and Y.-M. Wei, "A hybrid self-adaptive Particle Swarm Optimization–Genetic Algorithm–Radial Basis Function model for annual electricity demand prediction," *Energy Conversion and Management*, vol. 91, pp. 176-185, 2015.
- [57] C.-Y. Li, G. Zheng, and G.-P. Liu, "A real-time optimization control strategy for power management in fuel cell/battery hybrid power sources," presented at the International Conference on Control, Cardiff, United Kingdom, 2012.
- [58] O. Erdinc and M. Uzunoglu, "Optimum design of hybrid renewable energy systems: overview of different approaches," *Renewable and Sustainable Energy Reviews*, vol. 16, pp. 1412-1425, 2012.

- [59] D. Nelson, M. Nehrir, and C. Wang, "Unit sizing and cost analysis of standalone hybrid wind/PV/fuel cell power generation systems," *Renewable Energy*, vol. 31, pp. 1641-1656, 2006.
- [60] A. Kannan, A. Kabza, and J. Scholta, "Long term testing of start-stop cycles on High Temperature PEM Fuel cell stack," *Journal of Power Sources*, vol. 277, pp. 312-316, 2015.

7 CHAPTER 7: GENERAL DISCUSION

As stated in Section 2.5, the studies presented in this thesis were focused on the system level issues, which are inherited from the intermittent and unpredictable nature of wind and solar energy resources, when used as primary source in stand-alone hydrogen-based energy systems. The ultimate aim of this research project is investigating methodologies that use intelligent techniques to optimise the performance of such systems.

The central aim of the study presented in Chapter 3 was to develop a sizing methodology for stand-alone hydrogen systems. Studies on the design of renewable energy systems are readily available in the literature [1-15]. However, at the time that study undertaken, there was no study that uses maximising renewables penetration as an objective function when sizing stand-alone hydrogen systems. In addition, the impact of transient start-up time of fuel cells on system reliability has not been investigated. In Chapter 3, therefore, a multi-objective sizing methodology that incorporates maximising renewables penetration along with cost and environmental impact was proposed.

The overall objective of the research presented in Chapter 4 was to study the impact of training parameters on the accuracy of Neural Networks (NNs) when applied to short-term renewable energy forecasting. The application of NNs to predict short-term and long-term wind speed is one of the topics that attracted extensive research [16-21]. However, at the time this research was undertaken, there was no study that investigated the effect of using solar irradiance along with wind speed data for short-term wind speed forecasting. Moreover, there was no study that investigated the effect of wind speed seasonal variations on the NNs prediction accuracy. The findings of this study were later, in the work reported in Chapter 5 and 6, used to help realise a NN-based operation strategy for stand-alone hydrogen systems.

The third and fourth studies, described in Chapter 5 and Chapter 6, respectively, were focused on developing and experimentally validating a NN-based (intelligent) Power Management Strategy (PMS) for stand-alone hydrogen-based renewable energy systems. A PMS is crucial for the operation of a hybrid energy system and its ability to reliably meet load demand. Many comparisons and analysis of several Power Management Strategies (PMSs) for renewable energy systems can be found in the

literature [22-27]. However, the integration of predictive (intelligent) techniques into PMSs for renewable energy systems was rarely introduced. At the time this study was conducted, only two simulation studied have presented operation strategies that use a forecasting technique (persistence method) for controlling the power flow of hybrid renewable energy systems [28, 29] and no experimental validation was reported. Therefore, the validation and assessment of NN-based PMS for controlling stand-alone hydrogen-based renewable energy system is introduced in the third and fourth studies (Chapter 5 and Chapter 6, respectively) included in the thesis. The central research aim of the third study was to experimentally validate the NN-based PMS while the objective of the fourth study was to identify the possible impact of using such a strategy on the economic and operational aspects of stand-alone hydrogen systems.

7.1 DISCUSSIONS WITH REGARD TO THE RESEARCH OBJECTIVES

7.1.1 Research objective 1

To develop a multi-objective sizing methodology for stand-alone hydrogen systems that consider the reliability, renewables utilisation, environmental impact as well as the system cost using Genetic Algorithms (Chapter 3).

The finding of this study showed that ignoring the transient response of the prime mover (fuel cell) results in an overestimation of the reliability to meet an external electric load in stand-alone hydrogen-based renewable energy systems. Experiments showed that the fuel cell has a transient start-up time during which it cannot either totally or partially supply the requested demand. This start-up period may last for up to 2 minutes depending on the requested power. In stand-alone energy systems, the transient start-up time will appear as an interruption of the power supply whenever the fuel cell system is activated to supply power as it has been experimentally proven in the study presented in Chapter 5 (see Figure 5-8). Bearing in mind the intermittency of renewable resources, these interruptions may occur more often. Before this study was undertaken, all the proposed sizing methodologies of stand-alone hydrogen systems ignore the fuel cell transients [30-32] which questions their effectiveness. In fact, the results of this study showed that the reliability (expressed as the LPSP) of stand-alone hydrogen systems when neglecting the prime mover transients is more than double compared to when the transients are included. This highlights the necessity for a reliability index that considers the load losses during the transients of the system components. This study, therefore, contributes to the field by introducing a modified LPSP reliability index which accounts for the transient start-up characteristics of fuel

cells which will help researchers to more accurately assess the reliability of stand-alone hydrogen-based renewable energy systems. The mathematical formula of the modified LPSP index is shown in equation (3.2).

The multi-objective sizing methodology described in Chapter 3 including the modified LPSP reliability index was used to optimise three different configurations of stand-alone hydrogen systems when conjugated with and without battery storage and benchmarked against a single objective optimisation methodology that consider minimising the system cost only. The findings showed that unlike the ones consider cost only [33-35], sizing methodologies that minimise excess (dumped) energy does result in optimal solutions with higher renewables utilisation levels. For the wind/hydrogen, solar-PV/hydrogen and wind/solar-PV/hydrogen configurations optimised in this research, the amount of excess energy is 59%, 45% and 32%, respectively, when the optimisation aims to reduce the cost only. This finding, which is in agreement with previous published results [36], shows that the renewables utilisation levels are very low (less than 50% in some cases) and the systems are actually oversized. Yet no study had considered maximising renewables utilisation in the context of optimising stand-alone renewable energy system before this research was conducted. This study has proven that a significant improvement in renewables penetration levels can be achieved if the optimisation does not only aim to reduce the cost but also minimising the excess energy (in addition to cost). In addition, the results of this study agree with previous findings which show that stand-alone PV-H2 systems is not economically competitive compared to WG-H2 systems which acquire the best compromise between cost, renewables penetration and environmental footprint [37-39]. However, in order to increase renewables penetration, the sizing methodology presented in Chapter 3 tends to increase the capacity of the (costly) storage components which in turn increases the overall cost of the system. This result has led to a conclusion that in order to simultaneously improve the both the renewables utilisation and cost, a research for efficient strategies to manage the power flow within the stand-alone renewable energy systems is needed. In this regard, the literature indicate PMSs based on predictive techniques may help designing an efficient and cost-effective stand-alone renewable energy systems [28, 29]. Therefore, further research has been conducted to study the application of (intelligent) predictive techniques for improving the design and operation of stand-alone hydrogen-based renewable energy systems.

7.1.2 Research objective 2

To develop a methodology that uses readily available data at remote location for shortterm wind energy and wind power forecasting (using NN) and study the effect of seasonal variations of renewable resources on wind power predictions (Chapter 4).

The results presented in Chapter 4 are a determination of the best architecture and training parameters that allow higher accuracy of NNs when applied to short-term wind speed forecast. The impacts of four parameters: the span, resolution and type of training data as well as the Length of Training Pattern (LTP), on the performance of Feedforward (FF-NN) and Radial Basis Function (RBF-NN) were analysed. The results indicated that only one year span of hourly resolved wind speed and solar irradiance data are needed to achieve high accuracy of an hour-ahead wind speed predictions. No significant improvement can be achieved either by increasing the span or resolution. As with other types of NN models [40], this study proved that the prediction accuracy of the FF-NN and RBF-NN are also affected by their structure. The results have shown RBF-NN has prediction accuracy about one order of magnitude better than FF-NN which agrees with the finding of a previous research [41].

Another observation was that the accuracy of NN predictions is prone to seasonal variations of wind speed across the year if (only) wind speed data are used for training. One of the contributions of this research was proposing methodology to reduce the impact of seasonal variations on wind speed predication accuracy. The study presented in Chapter 4 proved that using solar irradiance along with wind speed data can help mitigate the seasonal influences. Unlike other meteorological data, solar irradiance can be easily predicted for geographical locations using well-established models such as ASHRAE [42]. This approach of including solar irradiance data when predicting wind speed can help accurately estimating the available wind power at any particular location, especially for remote areas where a record of other meteorological data may not be available. In addition, this approach may be useful for applications that involve series of short-term wind energy predictions span over several seasons such as predictive operation strategies for stand-alone renewable energy systems [28, 43].

7.1.3 Research objective 3

To develop and validate a NN-based (predictive) power management strategy for controlling the operation of stand-alone hydrogen based renewable energy systems (Chapter 5).

The experiments presented in Chapter 5 have provided an exploration into the effectiveness of using NN-based (predictive) Power Management Strategy (PMS) for controlling stand-alone renewable energy systems and the factors that influence the performance of such strategies which has not been previously reported. The key point of the examined predictive PMS is using predicted values of load demand and renewable power to estimate the future battery's state of charge based on which the activation/deactivation of the fuel cell unit is decided. Radial Basis Function Neural Network, which was proven to have high prediction accuracy by the study presented in Chapter 4, was used as a prediction tool to perform 30, 40, 50, 60 and 120 seconds ahead load demand and renewable power. Generally, the results of this study proved that predictive PMS can be used for controlling the operation of stand-alone hydrogenbased renewable energy systems over both transient and steady state stages. However, factors such as the accuracy of the prediction tool, prediction horizon, decision making interval of the PMS and measurement speed of the system variables must be carefully considered in order to effectively employ this type of operation strategies. This highlights the importance of choosing the right prediction tool when studying the incorporation of predictive operation strategies into renewable energy applications. It is well proven that NNs outperform other forecasting techniques such as persistence method [44]. This suggests that all studies that reported simulations of predictive operation strategies and employed persistence methods as prediction tools [28, 43] should be revisited by analysing the impact of the accuracy of the tool on the achieved results.

The results of this study also showed that the predictive PMSs can help avoid load supply interruptions that occur during the transient start-up time of back-up units. This can be attributed to the ability of predictive strategies to activates/deactivates the system components based on future anticipations of the system status which allows transient start-up times pass before an actual power is requested from the back-up units. PMSs that include forecasting techniques may be useful not only for avoiding load interruptions during transients of back-ups but also it may allow implementing operation strategies that make wiser decision by planning or scheduling the operation of the system components beforehand based on the forecasted values of the renewable resources and load demand which in turn may help increase the reliability and efficiency as well as reduce the system cost.

7.1.4 Research objective 4

Investigate the impact of NN-based (predictive) power management strategies on the economic and operational aspects of the system (Chapter 6).

The results of this study showed that NN-based (predictive) Power Management Strategy (PMS) impacts the system and operational characteristics of stand-alone hydrogen-based renewable energy systems. For sizing under the same load demand profile and reliability requirements, a stand-alone hydrogen system controlled by a predictive strategy was proven to possess lower cost of energy, less environmental footprint and higher renewables penetration compared to that controlled by rule-based (reactive) strategy. However, the advantages of the predictive PMS are pronounced only if the sizing algorithm targets high reliability levels and the transient dynamics are considered in the component models. The superiority of the predictive strategy may be rendered to its ability to mitigate the load losses during the transient-start-up time by activating the back-up units before an actual demand is requested. Unlike the results of the sizing methodology presented in Chapter 3 which used reactive strategy and showed that increasing renewables penetration comes at a cost [45], employing predictive PMS is proven to help maximise renewables penetration without compromising the system cost. The results also showed that predictive PMSs highly depend on the accuracy of the prediction tool employed to forecast the load demand and renewable energy resources which agreed with results reported in Chapter 5.

In conclusion, this thesis developed novel methodologies for optimising the size, integration and operational efficiency of hybrid, off-grid, renewable energy systems incorporating hydrogen-based technology. These techniques outperformed traditional approaches by drawing upon complex artificial intelligence and genetic models and included forecasting of renewable energy sources, such as wind speed, and energy storage. The proposed methodologies could underpin cost-effective, reliable power supplies to remote communities as well as reducing the dependence on fossil fuels and the associated environmental footprint

7.2 REFERENCES

- [1] J. Lagorse, D. Paire, and A. Miraoui, "Sizing optimization of a stand-alone street lighting system powered by a hybrid system using fuel cell, PV and battery," *Renewable Energy*, vol. 34, pp. 683-691, 2009.
- [2] H. Belmili, M. Haddadi, S. Bacha, M. F. Almi, and B. Bendib, "Sizing standalone photovoltaic–wind hybrid system: techno-economic analysis and

optimization," *Renewable and Sustainable Energy Reviews,* vol. 30, pp. 821-832, 2014.

- [3] A. Kaabeche and R. Ibtiouen, "Techno-economic optimization of hybrid photovoltaic/wind/diesel/battery generation in a stand-alone power system," *Solar Energy*, vol. 103, pp. 171-182, 2014.
- [4] H. Yang, L. Lu, and J. Burnett, "Weather data and probability analysis of hybrid photovoltaic–wind power generation systems in Hong Kong," *Renewable Energy*, vol. 28, pp. 1813-1824, 2003.
- [5] G. Tina and S. Gagliano, "Probabilistic analysis of weather data for a hybrid solar/wind energy system," *International Journal of Energy Research*, vol. 35, pp. 221-232, 2011.
- [6] G. Tina, S. Gagliano, and S. Raiti, "Hybrid solar/wind power system probabilistic modelling for long-term performance assessment," *Solar Energy*, vol. 80, pp. 578-588, 2006.
- [7] R. Dufo-López, J. L. Bernal-Agustín, and F. Mendoza, "Design and economical analysis of hybrid PV–wind systems connected to the grid for the intermittent production of hydrogen," *Energy Policy*, vol. 37, pp. 3082-3095, 2009.
- [8] D. K. Khatod, V. Pant, and J. Sharma, "Analytical approach for well-being assessment of small autonomous power systems with solar and wind energy sources," *IEEE Transactions on Energy Conversion*, vol. 25, pp. 535-545, 2010.
- [9] E. I. Zoulias and N. Lymberopoulos, "Techno-economic analysis of the integration of hydrogen energy technologies in renewable energy-based standalone power systems," *Renewable Energy*, vol. 32, pp. 680-696, 2007.
- [10] D. Nelson, M. Nehrir, and C. Wang, "Unit sizing and cost analysis of standalone hybrid wind/PV/fuel cell power generation systems," *Renewable Energy*, vol. 31, pp. 1641-1656, 2006.
- [11] C.-H. Li, X.-J. Zhu, G.-Y. Cao, S. Sui, and M.-R. Hu, "Dynamic modeling and sizing optimization of stand-alone photovoltaic power systems using hybrid energy storage technology," *Renewable Energy*, vol. 34, pp. 815-826, 2009.
- [12] S. M. Hakimi and S. M. Moghaddas-Tafreshi, "Optimal sizing of a stand-alone hybrid power system via particle swarm optimization for Kahnouj area in southeast of Iran," *Renewable Energy*, vol. 34, pp. 1855-1862, 2009.
- [13] D. B. Nelson, M. H. Nehrir, and C. Wang, "Unit sizing of stand-alone hybrid wind/PV/fuel cell power generation systems," in *IEEE Power Engineering Society General Meeting*, San Francisco, CA, USA, 2005, pp. 2116-2122.

- [14] Y. Katsigiannis, P. Georgilakis, and E. Karapidakis, "Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables," *IET Renewable Power Generation,* vol. 4, pp. 404-419, 2010.
- [15] R. Dufo-Lopez and J. L. Bernal-Agustin, "Multi-objective design of PV-winddiesel-hydrogen-battery systems," *Renewable Energy*, vol. 33, pp. 2559-2572, 2008.
- Y. Jiang, Z. Song, and A. Kusiak, "Very short-term wind speed forecasting with Bayesian structural break model," *Renewable energy*, vol. 50, pp. 637-647, 2013.
- [17] G. Li, J. Shi, and J. Zhou, "Bayesian adaptive combination of short-term wind speed forecasts from neural network models," *Renewable Energy*, vol. 36, pp. 352-359, 2011.
- [18] Z. Guo, W. Zhao, H. Lu, and J. Wang, "Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model," *Renewable Energy*, vol. 37, pp. 241-249, 2012.
- [19] H. B. Azad, S. Mekhilef, and V. G. Ganapathy, "Long-term wind speed forecasting and general pattern recognition using neural networks," *Sustainable Energy, IEEE Transactions on,* vol. 5, pp. 546-553, 2014.
- [20] J. Catalão, H. Pousinho, and V. Mendes, "Short-term wind power forecasting in Portugal by neural networks and wavelet transform," *Renewable Energy*, vol. 36, pp. 1245-1251, 2011.
- [21] A. M. Foley, P. G. Leahy, A. Marvuglia, and E. J. McKeogh, "Current methods and advances in forecasting of wind power generation," *Renewable Energy*, vol. 37, pp. 1-8, 2012.
- [22] E. Dursun and O. Kilic, "Comparative evaluation of different power management strategies of a stand-alone PV/Wind/PEMFC hybrid power system," *International Journal of Electrical Power & Energy Systems*, vol. 34, pp. 81-89, 2012.
- [23] K. Sopian, A. Zaharim, Y. Ali, Z. M. Nopiah, J. A. Razak, and N. S. Muhammad,
 "Optimal operational strategy for hybrid renewable energy system using genetic algorithms," WSEAS Transactions on Mathematics, vol. 7, pp. 130-140, 2008.
- [24] M. Safari and M. Sarvi, "Optimal load sharing strategy for a wind/diesel/battery hybrid power system based on imperialist competitive neural network algorithm," *IET Renewable Power Generation*, vol. 8, pp. 937-946, 2014.

- [25] K. H. Kang and D. J. Won, "Power management strategy of stand-alone hybrid system to reduce the operation mode changes," 2009, pp. 1-4.
- [26] A. Hajizadeh and M. A. Golkar, "Intelligent power management strategy of hybrid distributed generation system," *International Journal of Electrical Power* & Energy Systems, vol. 29, pp. 783-795, 2007.
- [27] D. Ipsakis, S. Voutetakis, P. Seferlis, F. Stergiopoulos, and C. Elmasides, "Power management strategies for a stand-alone power system using renewable energy sources and hydrogen storage," *International Journal of Hydrogen Energy*, vol. 34, pp. 7081-7095, 2009.
- [28] E. I. Vrettos and S. A. Papathanassiou, "Operating policy and optimal sizing of a high penetration RES-BESS system for small isolated grids," *IEEE Transactions on Energy Conversion*, vol. 26, pp. 744-756, 2011.
- [29] S. Yamamoto, K. Sumi, E. Nishikawa, and T. Hashimoto, "An Operating Method Using Prediction of Photovoltaic Power for a Photovoltaic-Diesel Hybrid Power Generation System," *IEEJ Transactions on Power and Energy,* vol. 124, pp. 521-530, 2004.
- [30] A. Maleki and A. Askarzadeh, "Artificial bee swarm optimization for optimum sizing of a stand-alone PV/WT/FC hybrid system considering LPSP concept," *Solar Energy*, vol. 107, pp. 227-235, 2014.
- [31] A. Maleki and A. Askarzadeh, "Comparative study of artificial intelligence techniques for sizing of a hydrogen-based stand-alone photovoltaic/wind hybrid system," *International Journal of Hydrogen Energy*, vol. 39, pp. 9973-9984, 2014.
- [32] A. Kashefi Kaviani, G. Riahy, and S. Kouhsari, "Optimal design of a reliable hydrogen-based stand-alone wind/PV generating system, considering component outages," *Renewable Energy*, vol. 34, pp. 2380-2390, 2009.
- [33] P. Bajpai, S. Kumar, and N. K. Kishore, "Sizing optimization and analysis of a stand-alone WTG system using hybrid energy storage technologies," in *Energy* and Sustainable Development: Issues and Strategies (ESD), 2010 Proceedings of the International Conference on, 2010, pp. 1-6.
- [34] A. E. S. A. Nafeh, "Optimal economical sizing of a PV-wind hybrid energy system using genetic algorithm," *International Journal of Green Energy*, vol. 8, pp. 25-43, 2011.
- [35] T. Ma, H. Yang, and L. Lu, "A feasibility study of a stand-alone hybrid solarwind-battery system for a remote island," *Applied Energy*, vol. 121, pp. 149-158, 2014.

- [36] J. A. Razak, K. Sopian, Y. Ali, M. A. Alghoul, A. Zaharim, and I. Ahmad,
 "Optimization of PV-wind-hydro-diesel hybrid system by minimizing excess capacity," *European Journal of Scientific Research*, vol. 25, pp. 663-671, 2009.
- [37] Z. Iverson, A. Achuthan, P. Marzocca, and D. Aidun, "Optimal design of hybrid renewable energy systems (HRES) using hydrogen storage technology for data center applications," *Renewable Energy*, vol. 52, pp. 79-87, 2013.
- [38] H. Caliskan, I. Dincer, and A. Hepbasli, "Exergoeconomic and environmental impact analyses of a renewable energy based hydrogen production system," *International Journal of Hydrogen Energy*, vol. 38, pp. 6104-6111, 2013.
- [39] M. Beccali, S. Brunone, M. Cellura, and V. Franzitta, "Energy, economic and environmental analysis on RET-hydrogen systems in residential buildings," *Renewable energy*, vol. 33, pp. 366-382, 2008.
- [40] G. Li and J. Shi, "On comparing three artificial neural networks for wind speed forecasting," *Applied Energy*, vol. 87, pp. 2313-2320, 2010.
- [41] T. Xie, H. Yu, and B. Wilamowski, "Comparison between traditional neural networks and radial basis function networks," in *International Symposium on Industrial Electronics (ISIE)*, Gdansk, Poland, 2011, pp. 1194-1199.
- [42] M. J. Ahmad and G. Tiwari, "Solar radiation models—A review," International Journal of Energy Research, vol. 35, pp. 271-290, 2011.
- [43] S. Yamamoto, K. Sumi, E. Nishikawa, and T. Hashimoto, "An operating method using prediction of photovoltaic power for a photovoltaic–diesel hybrid power generation system," *Electrical Engineering in Japan,* vol. 151, pp. 8-18, 2005.
- [44] T. G. Barbounis, J. B. Theocharis, M. C. Alexiadis, and P. S. Dokopoulos,
 "Long-term wind speed and power forecasting using local recurrent neural network models," *Energy Conversion, IEEE Transactions on*, vol. 21, pp. 273-284, 2006.
- [45] A. Brka, Y. M. Al-Abdeli, and G. Kothapalli, "The interplay between renewables penetration, costing and emissions in the sizing of stand-alone hydrogen systems," *International Journal of Hydrogen Energy*, vol. 40, pp. 125-135, 2015.

8 CHAPTER 8: GENERAL CONCLUSIONS

Power supply reliability under varying weather conditions and the cost of energy conversion technologies as well as the environmental impact are major concerns in designing modern hybrid renewable energy systems. In order to utilise the available wind and solar energy efficiently and economically, a multi-objective optimal sizing methodology is developed in this thesis based on Genetic Algorithm, which has the ability to obtain the global optima of complex non-linear problems with relative computational simplicity compared to conventional optimisation methods. The multi-objective sizing methodology is used to evaluate hydrogen-based hybrid renewable energy systems for off-grid applications, and to attain the system configuration which underpins the desired reliability with optimal compromise between cost, renewables penetration and environmental impact. A modified Loss of Power Supply Probability (LPSP) index, which account for load losses during transient start-up time of fuel cell units, is used to assess the reliability of meeting load requirements.

An effective operation strategy is a necessity for hybrid renewable energy systems to coordinate, and ensure stable and safe operation of the power generation, energy storage and backup units. This thesis has investigated the effectiveness of a Neural Network based Power Management Strategy (NN-based PMS) for controlling the power flow within stand-alone hydrogen-based renewable energy systems. As preparation for the implementation of NN-based (intelligent) PMS, an analysis of the prediction accuracy of Feed Forward and Radial Basis Function Neural Networks (FF-NN, RBF-NN), when applied for short-term renewable energy (wind) foresting, is presented. The research investigated the influences of the type, span and resolution of training data; and the Length of Training Pattern (LTP), on short-term wind speed prediction accuracy. The impact of the NN forecasting error on the estimation of renewable power generated by commercially available wind turbines is also studied. Then, the concept of NN-based PMS is validated experimentally by applying it to control (desktop) stand-alone hydrogen-based renewable energy system which has been specifically assembled for this purpose. The constructed (desktop) system consists of an emulated renewable power source, battery bank and fuel cell unit coupled to metal hydride hydrogen canisters. Following the experimental validation, the impact of NN-Based PMS on the economic and operational aspects of hydrogen-based renewable energy system is investigated.

The outcomes of the research reported in this thesis are summarised below:
- Sizing methodologies that ignore the start-up transients of back-up units overestimate the reliability to meet the load requirements. This research has introduced a modified LPSP index which may help researchers to more accurately evaluate the reliability of hydrogen-based stand-alone renewable energy systems.
- If the system is controlled by rule-based (reactive) PMS, sizing methodology that considers optimise renewables penetration and environmental footprint along with cost, of stand-alone hydrogen-based energy system results in configuration more expensive than that considers minimising cost only. The main reason is the high cost of energy storage devices.
- Wind/Hydrogen system configuration has the best compromise between the cost, renewables penetration and life cycle footprint compared to Solar-PV/Hydrogen and Wind/Solar-PV/Hydrogen configurations and incorporating limited battery storage within stand-alone hydrogen-based renewable energy systems reduces the total cost as well as the life cycle environmental impact.
- PMSs that depend on predictions of renewable resources and load demand (predictive PMSs) can effectively control the operation of hydrogen or hybridised energy systems and outperform rule-based strategies. However, the performance of such strategies is strongly influenced by the prediction horizon of load demand and renewable resources, accuracy of the prediction tool and the speed at which the system status is conveyed to the control unit.
- NNs are a good candidate to be used as a prediction tool for predictive PMSs as they can acquire high and consistent prediction accuracy regardless of the seasonal variations of renewable resources especially if a proper data and training methodology are used.
- Given the forecasting tool is highly reliable, using predictive PMS to control the operation of stand-alone hydrogen-based renewable energy system can help design more cost-effective, efficient and environmentally friendly system compared to reactive strategy.

Further investigations are warranted to study the impact of using NNs with multiple input parameters on the prediction of other renewable resources such as solar irradiance. Studies on the impact of using NNs on the ability to meet load requirements as well as the techno-economic and environmental impact of using a predictive PMS in Solar-PV or Wind/Solar-PV renewable energy systems are also needed.

9 APPENDICES

9.1 APPENDIX A

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9.2 APPENDIX B



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9.3 APPENDIX C



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9.4 APPENDIX D

Estimation of transient time of PEM fuel cell stack

Fuel cells use electrochemical reaction to produce electricity by combining hydrogen fuel with oxygen. The fuel cells have the advantages generating electricity by using combustion engines since they can generate electricity as long hydrogen fuel is supplied and because of the absence of the burning process, which happening in diesel generator, there are no harmful emissions. On the other hand, fuel cells are like batteries since they generate electricity from the interaction between chemical substances and the waste product is pure water. The efficiency of fuel cell technology is the double compared to combustion engines and use hydrogen as a fuel which is one of the simplest and most abundant elements on earth. Such a wealth of fuel represents an almost unlimited clean energy source.

There are several types of fuel cell. The most common types are the Proton Exchange Membrane Fuel Cell (PEMFC) and Solid Oxide Fuel Cell (SOFC). There are many literatures that describe the advantages of each type. This document considers the furthest developed and most commonly used fuel cell systems to experimentally test its transient dynamics (i. e. PEMFC).

PEMFC has an efficiency of around 50% and work at a moderate temperature of 80°. It has a compact design and achieves a high energy-to-weight ratio. However, limitations such as managing the operating temperature, freezing water and slow start-up when cold introduce some challenges to employ fuel cell in many applications. In the following, an experiment to estimate the cold start-up time of PEMFC stack is described.

Experimental set-up description

A diagram of the experimental set-up used to experimentally estimate the cold start-up time of PEMFC stack is shown in Figure. The set-up consists of Nexa 1200 PENFC stack, Power diode, electronic load, three metal hydride hydrogen canisters and PC for monitoring. The rated power of the used stack is 1.2kW and can supply 60 amperes maximum. The stack is equipped with cooling fan to maintain the operating temperature at an acceptable limit. The power diode is connected between the fuel cell

and the load. It is used as a safety device to protect the fuel cell from the reverse currents. The Heliocentris EL 1500 electronic load is used to draw a DC current from the fuel cell. This electronic load can be controlled manually or by software. The user can choose from three different operation modes, namely constant power mode (P-Mode), constant resistance (R-Mode) and constant current mode (I-Mode). The constant current operation mode (I-Mode) has been used in the experiment under consideration. Figure 2 shows the electronic load panel on which the duty of switches and displays are explained.



Figure A-1: The experimental set-up used to estimate the cold start-up time of Nexa 1200 fuel cell stack.



Figure A-2: External safety connection of Nexa 1200 fuel cell module without an external hydrogen sensor.

To operate the Nexa 1200 fuel cell module, a safety chain which includes an external hydrogen sensor must be accomplished at the safety chain connectors on the back of the module. To establish an external safety chain without an external H2-sensor, two bridges between pin 1 & 2 and 3 & 4 of the "Safety Chain" connector must be established as shown in Figure 4.

To estimate the cold start-up time of PEMFC, the transient performance of Nexa 1200 PEMFC is studied by measuring the output voltage from the entire stack for step changes in load currents between 0-3A, 0-6A, 0-12A, 0-15A, 0-20A, 0-25A, 0-30A, 0-35A, 0-40A and 0-45A. The following figures show the load current and the stack voltage measured during the transient operation of the stack. For each step change current, the fuel cell stack is left to cool down first for at least two hours before conducting the next measurements.

9.5 APPENDIX E

Optimising Renewables Utilisation in Sizing Stand-alone Power Systems with Batteries

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ABSTRACT

This paper examines the size optimisation of stand-alone renewable power systems with battery storage in the context of maximising renewables penetration. The systems assessed use wind turbines and/or solar panels for power generation and batteries as backup. The sizing process is formulated as a multi-objective problem and solved using the Genetic Algorithms optimisation technique (GA). Loss of Power Supply Probability (LPSP) is used to assess the reliability of the considered systems. In addition, a comparison to a single objective sizing method (minimising Net Present Cost only) is established. The results indicate that incorporating an objective function to increase renewables penetration during the sizing of renewable energy systems supported by batteries improves the overall system efficiency but the total cost is increased. Furthermore, the systems designed by considering minimising excess energy are more susceptible to the intermittency of renewable resources compared to the sizing using an economic objective only. The yields also indicate that Wind/PV-Battery represents the most economic and efficient configuration to supply the target load at the location considered.

1- INTRODUCTION

Renewable energy resources such as solar and wind are abundant and minimise environmentally harmful emissions when generating electric power. Wind and solar energies are promising solution to supply electricity for remote and rural communities [1]. They can also reduce public power grid infrastructure. Unfortunately, renewable energy resources particularly wind and solar irradiance can be intermittent and unpredictable [2] leading to poor reliability compared to traditional ones. Several approaches have been followed to tackle the drawbacks of renewable energy sources. Accordingly, wind and solar power sources are often combined with energy storage devices such as batteries to improve power supply reliability albeit with higher system cost and complexity. Conversely, appropriate system size can help optimise reliability and cost.

Numerous studies have explored optimal sizing of renewable energy systems, on the basis of cost and reliability, by using intelligent techniques such as Particle Swarm Optimisation (PSO) [3], Simulated Annealing (SA) [4] or Genetic Algorithms (GA) [5]. For example, Kaviani et al [6] employed PSO to minimise the annual cost of a hybrid wind-PV-hydrogen renewable energy system. The reliability to meet demand was evaluated using Loss of Load Expected (LOLE) and Loss of Power Supply Probability (LPSP). PSO was also used in combination with Harmony Search (HS) for optimally sizing hydrogen based renewable energy system [7] as indicated by Net Present Cost (NPC) and Equivalent Loss Factor (ELF) for system reliability. Although cost is an important design constraint, other aspects such as minimising life cycle greenhouse gas outputs through using renewable energy systems are also important. Multiobjective optimisation of renewable energy systems has been attempted by many researchers, including Katsigiannis et al [8] who minimised Cost of Energy (COE) and Life Cycle Emissions (LCE) concurrently for small hybrid power systems. Dufo-Lopez and Bernal-Agustin [9] enhanced the optimisation objectives by minimising the unmet load to size a stand-alone PV-wind-diesel system, with battery storage, efficiently.

The above studies have not considered system conversion efficiency and associated design issues when optimising stand-alone hybrid renewable energy systems [10]. Generally, researchers assume a dump load is connected to stand-alone renewable energy systems in order to dispose of excess energy (kW-hr) [11, 12] which may reach 50% of the generated power [10]. Although wind and solar energy resources are free, converting these resources into useful electric power is costly. Therefore, minimising the excess (dumped) power is important because it may reduce energy conversion cost. This paper investigates the effectiveness of incorporating minimisation of the percentage of excess (dumped) energy, along with related system costs, to design an efficient and cost effective stand-alone renewable energy system with battery storage. The sizing optimisation problem is formulated as a multi-objective problem and solved using Genetic Algorithm optimisation technique.

The paper is outlined as follows. Section 2 presents a description of system component models. Section 3 describes the energy management strategy. The sizing optimisation problem is explained in Section 4 while the results and conclusions in Section 5 and Section 6 respectively.

2- MODELLING OF SYSTEM COMPONENTS

In order to evaluate the effect of considering minimising the excess energy during sizing renewable energy systems, three different configurations of renewable energy systems have been modelled. These configurations are:

Wind/Photovoltaic-Battery (WG/PV-BAT)

Photovoltaic-Battery (PV-BAT)

Wind-Battery (WG-BAT)

Figure 1 shows block diagrams of the considered hybrid renewable energy system followed by the models of the system components.



Figure 1: Block diagram of the considered renewable energy systems. (a) WG/PV-

BAT.

(b) PV-BAT. (c) WG-BAT.

2-1 Wind turbine

The output power of the wind turbine is determined by the wind speed at the hub height and the output characteristics curve provided by the manufacturer. The wind speed at the hub height is commonly calculated through exponent law [13]:

$$\frac{v}{v_0} = \left(\frac{H}{H_0}\right)^{\alpha} \tag{1}$$

Where, v is the wind speed at the desired height z, v_0 is the wind speed at the reference height z_0 , α is the shear coefficient and its typical value for low roughness land is 1/7 [13].



Figure 1: Wind turbine power curve [14].

The characteristics equation can be derived from the power curve using binomial fitting. The power curve of the wind turbine that used in this study is extracted from the manufacturer datasheet and it is depicted in Figure 1. The technical characteristics of the wind turbine that is used in this work are listed in Table 1.

Parameter	Value
Rated power	2 (kW)
Cut-in speed	3 (m/s)
Rated speed	9 (m/s)
Generator efficiency	>80 (%)
Tower height	18 (m)

Table 1: Technical characteristics of 2kW wind turbine [15]

2-2 Solar panel

In this study, a single photovoltaic cell is modelled using a single diode circuit as shown in Figure 2.



Figure 2: Single-diode model for photovoltaic cell.

The following equation represents the current-voltage characteristics of a practical photovoltaic device [16]:

$$I_{PV} = I_{PV,cell} - I_{0,cell} \left[e^{\frac{q(V+IR_s)}{KT}} - 1 \right]$$
(2)

Where $I_{PV,cell}$ is the current generated by incident light, $I_{0,cell}$ is the reverse saturation current of the diode, q is the electron charge, K is Boltzmann constant, and T is the temperature. Apart from the two resisters, the parameters of solar model can be determined directly from the datasheet. The resister R_s can be estimated from I-V curve provided by the manufacture. Solar radiation data are predicted using the wellknown ASHRAE model [17] and the effect of the ambient temperature is neglected. Finally, the solar module consists of 36 cells connected in series and the output power of the panel can be expressed as follows:

$$P_{PV} = NI_{PV}V \tag{3}$$

where, N is the number of the cells connected in series. The technical characteristics of the solar module used in this research are depicted in Table 2 [18].

Parameter	Value
Rated power P _{MAX}	135 (W)
Temperature (T _{CELL})	48.2 (°C)
Short circuit current (Isc)	8.33 (A)
Reverse current (I _R)	15 (A)
Open circuit voltage (Voc)	21.56 (V)
Number of cells	36
Efficiency (η)	13.61 (%)

Table 2: Technical characteristics of the solar panel module [18]

2-3 Lead acid battery

The battery plays the role of an energy buffer to absorb the short-term fluctuations of the renewable sources. Different models for batteries are available in the literature [11, 19]. The model described in [20] uses data from the manufacturer's datasheet to simulate the dynamic performance of the lead-acid battery. In the state of charge, the battery voltage is given by the following equation:

$$V_{bat} = E_0 - R.i - K \frac{Q}{Q-it}.(it + i^*) + Exp(t)$$
(4)

On the other hand, in the state of discharge, the battery voltage can be expressed as:

$$V_{bat} = E_0 - R.i - K \frac{Q}{it - 0.1Q} \cdot i^* - K \frac{Q}{Q - it} \cdot it + Exp(t)$$
(5)

where, E_{bat} is the battery voltage, E_0 is the battery constant voltage, K is the polarisation constant, Q is the battery capacity, R is the battery's internal resistance. To prolong the battery lifetime, the battery should not be overcharged or over discharged. This means that the state of charge of the battery must be kept into predefined upper and lower limits. The State Of-Charge (SOC) of the battery can be calculated as [20]:

$$SOC = \left(1 - (1/Q) \int_0^t i(t)dt\right) \times 100 \,(\%) \tag{6}$$

The technical characteristics of the battery module used in this work are listed in Table

Parameter	Value
Nominal voltage	12 (v)
Nominal capacity	55 (Ah)
Internal resistance	3.5 Ω
Efficiency	80 (%)

Table 3: Technical characteristics of the battery module

Lead-acid battery has been modelled assuming depth of discharge equal to 60% [19].

2-4 DC/AC Inverter

An inverter converts DC electrical power to an AC form. In this study, the DC/AC inverter is modelled using its efficiency (μ_{inv}) as follows:

where, $P_{inv,Load}$ is the power delivered to the load from the inverter and $P_{in,inv}$ is the inverter's input power.

3- ENERGY MANAGEMENT STRATEGY

The energy management strategy is developed based on the energy balance throughout the year. The energy produced by the renewable sources (Wind and/or PV) is compared with the load demand to determine the flow of energy between the load and the battery. If the battery bank is fully charged, the surplus is dumped on a dummy load. In case there is a deficit; it will be drawn from the battery bank. A flow chart for the employed energy management strategy is shown in Figure 4.





4- OPTIMISATION PROBLEM FORMULATION

The sizing methodology employs multi-objective genetic algorithm technique which dynamically searches for the optimal configuration that satisfies two objectives among several commercially available components. These objectives are minimising the system's Net Present Cost (NPC) and minimising the excess (dumped) energy. The optimal system must also satisfy some constraints as explained in the following.

$$F = min \{NPC, P_{excess}\}$$

(8)

Where, *NPC* and P_{excess} are the total NPC and excess energy respectively and are calculated as follows:

4-1 Minimisation of total NPC

The NPC of a system is the present value of all the costs that incurs over their lifetimes, which include the capital, replacement, operation and maintenance costs, minus the salvage value of the system components at the end of the project lifetime. The net present cost for the system components can be expressed as [6, 21]:

$$NPC_i = N_i \times \left(C_{cap} + C_{rep} \times K_i(ir, L_i, y_i) + C_{o\&m} \times CRF(ir, R)\right)$$
(9)

In this regard, *N* is the number of units, C_{cap} is the capital cost, C_{rep} is the replacement cost, and $C_{o\&m}$ is the annual operation and maintenance cost of the component. *ir* is the interest rate (here, 6%), and *R* is the project lifetime. *CRF* and *K* are capital recovery factor and single payment present worth which are defined as follows:

$$CRF(ir, R) = ir \times (1 + ir)^{R} / ((1 + ir)^{R} - 1)$$
(10)

$$K_i(ir, L_i, y_i) = \sum_{n=1}^{y_i} 1/(1+ir)^{n \times L_i}$$
(11)

Where, L is the component's lifetime and y is number of replacements of the component during the lifetime of the project which is a simple function of lifetime of the component and the project. The total net present cost is the sum of the net present cost of the system components.

$$NPC_{total} = \sum_{i} NPC_{i} \tag{12}$$

The cost, lifetime and size for the components used in the sizing process are presented in Table 4.

Component	Size	Capital	Replacement	O&M	Lifetime
Wind turbine	2kW	\$10200	\$7000	\$140	15yr
Solar panel	135W	\$310	\$310	0	25yr
Lead-acid battery	55Ah,12V	\$120	\$120	\$20	5yr
Converter	1KW	\$800	\$750	\$8	15yr

Table 4: The costs and lifetime of the system components [22, 23]

4-2 Minimisation of excess energy

The amount of excess (dumped) energy that the system produces is the energy that is not consumed by the useful load or stored in the storage devices. The total excess energy generated by the system can be expressed as follows:

$$E_{excess} = \sum_{t=1}^{8760} P_{excess}(t) \,\Delta t \tag{13}$$

The percentage of excess energy from that originally (renewably) derived is then calculated as:

$$EE = \left(E_{excess} / \sum_{t=1}^{T} P_{ren}(t) \,\Delta t\right) \times 100 \quad (\%)$$
(14)

Where, P_{ren} is the power generated by the renewable source and can be calculated as follows:

$$P_{ren} = \begin{cases} P_{WG}(t) + P_{PV}(t); & For WG/PV - BAT system \\ P_{PV}(t); & For PV - BAT system \\ P_{WG}(t); & For WG - BAT system \end{cases}$$
(15)

4-3 Problem Constraints

The optimisation problem is subject to the following Constraints:

$$N_{i,min} \le N_i \le N_{i,max} \tag{16}$$

$$LPSP = LPSP_{limit} \tag{17}$$

LPSP measures the reliability of the energy system and can be defined as the ratio of all energy deficits to the load demand during the considered period where an LPSP of 1 means the load will never be satisfied while LPSP of 0 means the load will be always satisfied. The LPSP index can be expressed by the following [11].

$$LPSP = \sum_{t=1}^{8760} LPS(t) / \sum_{t=1}^{8760} P_{Load}(t)$$
(18)

Where, LPS(t) is the deficit of the power supply at hour *t* and P_{Load} is the load demand. In this study, the LPSP constraint is chosen to be 0.1 ± 0.005 for all considered standalone systems. This range has been chosen to ensure that all the resultant solutions have the same reliability.

4-4 Optimal compromise solution

Fuzzy membership function is used to determine the best compromise solution among the Pareto front solutions. The value of the membership function μ_i is defined as [24]:

$$\mu_{i} = \begin{cases} 1 & F_{i} \leq F_{i}^{min} \\ \frac{F_{i}^{max} - F_{i}}{F_{i}^{max} - F_{i}^{min}} F_{i}^{min} & < F_{i} < F_{i}^{max} \\ 0 & F_{i} \geq F_{i}^{max} \end{cases}$$
(19)

Where F_i^{min} and F_i^{max} are the minimum and maximum value of the *i*th objective function. For each non-dominant solution, the normalised membership function μ^k is calculated as:

$$\mu^{k} = \frac{\sum_{i=1}^{N_{obj}} \mu_{i}^{k}}{\sum_{k=1}^{N_{obj}} \sum_{i=1}^{N_{obj}} \mu_{i}^{k}}$$
(20)

In this regard, M is the number of non-dominated solutions and N_{obj} is the number of objective functions. The best compromise solution is the one that have the maximum value of the normalised membership function.

4-5 Genetic Algorithm implementation

Multi-objective genetic algorithm toolbox (MATLAB R2012b) is used to solve the previous optimisation problem. A MATLAB code represents the fitness function, which calculates the values of all objectives, has been written as an M-file. In addition, the algorithm is adopted to eliminate all solutions that do not satisfy the reliability constraint. Bounds on the number of components are entered directly in the dedicated position in the toolbox. Because the optimisation problem in and is an integer problem, three other M-files represent the creation, mutation and crossover functions that generate integer numbers satisfy the problem constraints are also incorporate into the optimisation algorithm. The used settings in the multi-objective tool are 4 subpopulations with 100 individuals each for the population size, the crossover probability is 80% and the number of generation is 100. The optimisation variables are the numbers of solar modules, wind turbines and batteries. The optimisation algorithm repeatedly changes the values of the optimisation variables and simulates the system performance by calling a Simulink model for the stand-alone renewable energy system.

5- RESULTS AND DISCUSSION

Hourly resolved wind speed, solar irradiance data, which belong to a remote location in Western Australia (latitude: -31.75°, longitude: 115.8°),. The wind speed data, Figure 5, are measured by the Australian Bureau of meteorology [25] while solar irradiance data, Figure 6, are estimated using the well-known ASHRAE clear sky model [26] because measured data are not available. The optimisation process is led by measure load demand of a Western Australian household.







Figure 6: Hourly solar irradiance with t=0 corresponding to 00:00 on 1st Jan.

Three different configurations are optimally sized, namely WG/PV-BAT, PV-BAT and WG/PV-BAT renewable energy systems. Two design methods named Design Method-1 and Design Method-2 are used to size the considered configurations. The first optimises the NPC only while the second optimises NPC and EE. The reliability constraint (LPSP) is set equal to 0.01±0.005 for all considered configurations. For each

configuration, the optimisation algorithm is run to find the optimal number of system components that satisfies the reliability constraint.



Figure 7: Fitness function convergence for WG/PV-BAT optimised with Design Method-1.



Figure 8: Fitness function convergence for WG/PV-BAT optimised with Design

Method-2.

The corresponding fitness function optimisation of Design Method-1 (NPC optimisation) and Design Method-2 (NPC and EE optimisation), for WG/PV-BAT configuration, along the successive generations of the GA are shown in Figure 7 and Figure 8 respectively. These figures indicate that the system sized with one objective only is optimised faster than the one with multi-objective sizing which reveal that Design Method-2 is more complicated than Design Method-1.

The sizing results for WG/PV-BAT, PV-BAT and WG/PV-BAT configurations are listed in Table 5, Table 6 and Table 7, respectively. It can be observed that energy storage

units (battery) in PV-BAT system are highest compared to WG-Bat and WG/PV-BAT system. This may rendered to the fact that solar energy is not available at night-time and more energy storage capacity is needed to supply power during this period. On the other hand, the optimal solutions for WG/PV-BAT have least energy storage capacity perhaps because wind and solar energy resources complement each other therefore batteries are used to supply the load for less time periods. Another observation is that the number of power generation units (Wind turbines and solar modules) resulted from Design Method-1 is more than the corresponding units resulted from Design Method-1 is less compared to Design Method-2.

Table 5: Optimal solution for a WG/PV-BAT renewable energy system, LPSP=0.01±0.005

Design method	Wind turbine (units)	PV (units)	Battery (units)	Converter (kW)
Design Method-1: min(NPC)	1	49	48	5
Design Method-2: min(NPC, EE)	1	35	76	7

Table 6: Optimal solu	ition for a PV-BAT	renewable energy s	system, LPSP=0.01±0.005
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Design method	PV	Battery	Converter
	(units)	(units)	(kW)
Design Method-1: min(NPC)	95	56	5
Design Method-2: min(NPC, EE)	65	116	7

 Table 7: Optimal solution for a WG-BAT renewable energy system, LPSP=0.01±0.005

Design method	Wind turbine (units)	Battery (units)	Converter (kW)
Design Method-1: min(NPC)	4	56	5
Design Method-2: min(NPC, EE)	3	100	5



Figure 9: The percentages of excess (dumped) energy for the optimal solutions from Design Method-1.

Figure 9 shows the percentages of excess (dumped) energy for optimal solutions resultant from Design Method-1. This figure reveals that when a renewable energy system is optimised by cost only optimisation methodology (Design Method-1), a considerable amount of the renewably generated power is not consumed by the useful load. This implies that the generation units are oversized and part of the system's cost is actually "dumped". Figure 10 shows a comparison between the annual NPC and Annual Cost of Excess Energy (COEE) for the optimal solutions of the systems sizing results from Design Method-1.



Figure 10: Comparison between the Annual COEE and annual NPC for systems optimised with Design Method-1.





Hypothetically, it may be anticipated that reducing the COEE will reduce the total cost of the energy system. To assess this hypothesis, Design Method-2 which considers minimising EE along with NPC of the energy system is employed. By reaching a solution with less excess (dumped) energy, this sizing methodology may lead to designing less expensive renewable energy systems.

Figure 11 shows a comparison between the total NPC of the optimal solutions from Design Method-1 and Design Method-2. Although Design Method-2 results in systems with less excess (dumped) energy (43%, 47%, and 55% for WG/PV-BAT, PV-BAT and WG-BAT respectively), the total NPC of optimal solutions archived by this method are more expensive than optimal solutions of Design Method-1. To investigate the reason behind this unexpected result, capital cost of primary generation units (\$), capital cost of batteries (\$) and percentage of Excess Energy (%) of WG/PV-BAT are compared and depicted in Figure 12.



Figure 12: Comparison between the capital cost of generation units, capital cost of batteries and the percentage of excess energy of WG/PV-BAT configuration.

As can be observed, while Design Method-2 results in a slight reduction of the capital cost of energy generation units (wind turbines and solar modules), the capital cost of storage units (batteries) is significantly increased. Consequently, savings gained from reducing energy generation movers are significantly less than the increment of energy storage cost. This is because solutions from Design Method-2 have more storage units compared to Design Method-1. This result reveals that minimising excess energy is not preferable option when optimising stand-alone renewable energy systems with battery storage due to the high cost of energy storage units. Moreover, solutions from Design Method-2 are more susceptible to the changes of the renewable energy resources. Figure 13 shows the effect of reducing the amount of solar irradiance (by 5%, 10% and 15%) on the reliability of PV-BAT system sized by Design Method-1 and Design Method-2. It is clear that for the solution from Design Method-2, the LPSP increases when the level of solar irradiance decreases while no considerable change happens to the system designed using Design Method-1. It should be noted here that higher LPSP means less system reliability.



Figure 13: The effect of renewable resource reduction on PV-BAT system reliability

By comparing the achieved optimal solutions, it has been found that renewable energy system that uses solar panels with battery storage (PV-BAT) is not economically favourable compared to the other configurations. The most favourable configuration from economic point of view is the system consists of hybridisation of wind turbines and solar panels with battery storage. This result agrees with previously published results [11]. This study has shown that considering minimising the excess energy when designing renewable energy system with battery storage is not preferable for the time being because of the high cost of energy storage units.

6- CONCLUSIONS

This paper presents a comparison between single and multi-objective sizing methods of three stand-alone renewable energy systems incorporating battery storage (Wind turbine/Solar panel-Battery, Solar panel-Battery and Wind turbine-Battery) in the context of optimising renewables penetration. The first sizing method (Design Method-1) considers minimising Net Present Cost (NPC) only while the second considers minimising the Excess (dumped) Energy (EE) along with NPC. The concept of Loss of Power Supply Probability (LPSP) is used as a measure of load supply reliability. The results yield that Wind/PV-battery is the most economically preferable configuration with the least percentage of dumped energy given the specific load and location considered in this study. The results yield, also, incorporating an objective to minimise excess energy during the sizing of renewable energy systems with battery storage increases renewables penetration. However, the resulted system is more expensive and more susceptible to the variations of renewable resources.

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8- REFERENCES

[1] E. Koutroulis, D. Kolokotsa, A. Potirakis, and K. Kalaitzakis, "Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms," *Solar Energy,* vol. 80, pp. 1072-1088, 2006.

[2] A. Brka, Y. M. Al-Abdeli, and G. Kothapalli, "Influence of neural network training parameters on short-term wind forecasting," *International Journal of Sustainable Energy*, pp. 1-17, 2014. http://dx.doi.org/10.1080/14786451.2013.873437.

[3] M. Sharafi and T. Y. ELMekkawy, "Multi-objective optimal design of hybrid renewable energy systems using PSO-simulation based approach," *Renewable Energy*, vol. 68, pp. 67-79, 2014.

[4] O. Ekren and B. Y. Ekren, "Size optimization of a PV/wind hybrid energy conversion system with battery storage using simulated annealing," *Applied Energy,* vol. 87, pp. 592-598, 2010.

[5] D. Feroldi and D. Zumoffen, "Sizing methodology for hybrid systems based on multiple renewable power sources integrated to the energy management strategy," *International Journal of Hydrogen Energy*, 2014.

[6] A. Kashefi Kaviani, G. Riahy, and S. Kouhsari, "Optimal design of a reliable hydrogen-based stand-alone wind/PV generating system, considering component outages," *Renewable Energy*, vol. 34, pp. 2380-2390, 2009.

[7] S. Dehghan, B. Kiani, A. Kazemi, and A. Parizad, "Optimal sizing of a hybrid wind/PV plant considering reliability indices," *World Academy of Science, Engineering and Technology,* vol. 56, pp. 527-535, 2009.

[8] Y. Katsigiannis, P. Georgilakis, and E. Karapidakis, "Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables," *Renewable Power Generation, IET*, vol. 4, pp. 404-419, 2010.

[9] R. Dufo-Lopez and J. L. Bernal-Agustin, "Multi-objective design of PV–wind– diesel–hydrogen–battery systems," *Renewable Energy,* vol. 33, pp. 2559-2572, 2008.

 [10] J. A. Razak, K. Sopian, Y. Ali, M. A. Alghoul, A. Zaharim, and I. Ahmad,
 "Optimization of PV-wind-hydro-diesel hybrid system by minimizing excess capacity," *European Journal of Scientific Research*, vol. 25, pp. 663-671, 2009.

[11] A. E. S. A. Nafeh, "Optimal economical sizing of a PV-wind hybrid energy system using genetic algorithm," *International Journal of Green Energy*, vol. 8, pp. 25-43, 2011.

[12] D. Xu, L. Kang, L. Chang, and B. Cao, "Optimal sizing of standalone hybrid wind/PV power systems using genetic algorithms," in *Canadian Conference on Electrical and Computer Engineering*, 2005, pp. 1722-1725.

[13] B. S. Borowy and Z. M. Salameh, "Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system," *IEEE Transactions on Energy Conversion*, vol. 11, pp. 367-375, 1996.

[14] B. Escobar, J. Hernández, R. Barbosa, and Y. Verde-Gómez, "Analytical model as a tool for the sizing of a hydrogen production system based on renewable energy: The Mexican Caribbean as a case of study," *International Journal of Hydrogen Energy,* vol. 38, pp. 12562-12569, 2013.

[15] Anhui Hummer Dynamo Co. Ltd. (05.07.2012). *Hummer*. Available: http://www.china-windturbine.com/about.htm

[16] D. Sera, R. Teodorescu, and P. Rodriguez, "PV panel model based on datasheet values," in *IEEE International Symposium on Industrial Electronics*, Vigo, Spain, IEEE, 2007, pp. 2392-2396.

[17] K. Bakirci, "Estimation of solar radiation by using ASHRAE clear-sky model in Erzurum, Turkey," *Energy Sources, Part A,* vol. 31, pp. 208-216, 2009.

[18] Heliocentris. (15.03.2012). Available: http://www.heliocentris.com/

[19] S. Pedrazzi, G. Zini, and P. Tartarini, "Complete modeling and software implementation of a virtual solar hydrogen hybrid system," *Energy Conversion and Management*, vol. 51, pp. 122-129, 2010.

[20] O. Tremblay and L.-A. Dessaint, "Experimental validation of a battery dynamic model for EV applications," *World Electric Vehicle Journal*, vol. 3, pp. 13-16, 2009.

[21] Homer Energy. (2012). *Homer, (version 2.68 beta)*. Available: http://homerenergy.com/software.html

[22] M. J. Vasallo, J. M. Andújar, C. Garcia, and J. J. Brey, "A methodology for sizing backup fuel-cell/battery hybrid power systems," *IEEE Transactions on Industrial Electronics*, vol. 57, pp. 1964-1975, 2010.

 P. Hearps and D. McConnell. (2013, Renewable energy technology cost review.
 Rep., 1-58. Available: http://www.garnautreview.org.au/update-2011/commissionedwork/renewable-energy-technology-cost-review.pdf

[24] Z. Bo and C. Yi-jia, "Multiple objective particle swarm optimization technique for economic load dispatch," *Journal of Zhejiang University SCIENCE A,* vol. 6, pp. 420-427, 2005.

[25] BOM. (20. 07. 2011). *Western Australia weather and warnings*. Available: http://reg.bom.gov.au/wa/

[26] L. Wong and W. Chow, "Solar radiation model," *Applied Energy,* vol. 69, pp. 191-224, 2001.

9.6 APPENDIX F

Sizing of an equivalent fuel cell/hydrogen system matching wind power

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This appendix was published as an article in the thirteenth postgraduate electrical engineering & computing symposium, 2012. Whilst all efforts were made to retain the original features of this article, minor changes such as the layout, number formats, and font size and style were implemented in order to maintain consistency in the formatting style of the thesis.

Abstract— Hydrogen is an energy carrier which provides one means of mitigating against the intermittent nature of renewable sources, such as wind and solar energy, by providing a media for seasonal energy storage. This paper presents an analysis for the sizing of hydrogen storage capacity model to match the wind energy potential in a stand-alone fuel cell/hydrogen energy system. The research uses Matlab/Simulink to help build a (steady-state) model for the hydrogen storage capacity and fuel cell equivalent needed to offset an annual wind energy yield. Using actual hourly resolved wind speed data and a manufacturer's power curve for a wind turbine, the annual wind power profile is simulated. The resultant profile is used to determine the number of fuel cell units needed and the volume of hydrogen consumed. Results show that a fuel cells/hydrogen energy system outweighs the equivalent wind power system in terms of conversion efficiency.

Index Terms— Sizing; Wind energy; Fuel cells; Hydrogen.

INTRODUCTION

Energy availability has become an important part of modern life. In this regard, the issues of consumption and emissions related to using fossil fuel stimulate extensive research for possible substitutes. Wind and solar energy represent a clean and abundant alternative energy source to fossil fuels. However, their intermittent and seasonal nature makes them unreliable. To meet the reliability requirements, storage systems have been used to store surplus energy during the low demand hours, provide long-term storage capacity or simply augment instantaneous power generated where a mismatch exists between renewable energy and total load. Several devices can be

used as energy storage such as batteries, flywheels and hydrogen tanks. The size of the storage device should be carefully chosen to ensure supplying any partial shortage of power, but also to provide sufficient power during power outage periods of the main source such as occurs at nighttime if solar-PV systems are relied upon.

Several studies have been published on sizing energy storage devices for hybrid power systems. Optimal size of battery storage for wind-diesel power system has been investigated by Elhadidy and Shaahid [1]. Results from this study showed that the operational time of a diesel generator can be reduced by more than 50% if one day of battery storage is used. Loss of Power Supply Probability (LPSP) techniques have also been used for sizing batteries [2] and adopted by Nelson et al. [3] to determine the number of hydrogen storage tanks required for wind/PV/fuel cell power generation system. The proposed approach is easy to implement but it depends on the availability of time series data of the renewable resources (wind and PV).

The aim of this paper is to size fuel cells/hydrogen system capable of producing the same power generated by an equivalent wind turbine over one year. The paper is divided as follows: Section II describes the methodology; Section III simulates results and section IV gives the overall conclusions.

METHODOLOGY

Wind data and wind turbine model

The wind data used in this study consists of one year hourly resolved data measured by the Bureau of Meteorology (BOM) at a height of 10 meters at the Ocean Reef meteorological station (Western Australia, Latitude: -31.750, Longitude: 115.80) [4]. Fig. 1 shows the wind speed profile.



Fig. 1. Hourly averaged wind speed (Ocean Reef, Western Australia for 1997) [4].

The maximum available wind power from a wind turbine can be calculated using the following equation [5]:

$$P_W = 0.5\rho AV^3 \tag{1}$$

Where ρ is the air density, *A* is the swept area and *V* is the wind speed. However, the actual generated power is less due to the efficiency of the wind power conversion system. To obtain the actual output power, a polynomial fit to the power characteristics of a wind turbine can be used. In this paper, a 2.4 kW wind turbine is considered [6] and the characteristics power-vs.-wind speed curve is depicted in Fig. 2. Table I also shows the basic operating parameters of this turbine.



Fig. 2. Wind turbine manufacturer's power curve [6].

Table I: Basic parameters of the wind turbine [6].

Rated capacity	2.4 KW
Swept area	10.87 m ²
Cut-in wind speed	3.5 m/s
Turbine height	10 m
Rated wind speed	13 m/s

Fuel cell model

A Proton Electrolyte Membrane (PEM) fuel cell uses hydrogen fuel and is capable of yielding electric power through electrochemical process. In this study, the Ballard 1.2 kW Nexa fuel cell has been considered and all parameters for this fuel cell are listed in

Table 1. A dynamic model of the aforementioned fuel cell system is retrieved from the literature [7]. The equations of the used model are rewritten below and more details can be found in [8]. The output voltage of the fuel cell is given as:

$$V_{fc} = x_{\Gamma} + x_2(T_{st} - T_{st}^0) + x_3(0.5\ln(po_{2,ca}) + \ln(p_{H_2})) - x_4(1 - \exp(-j/x_5)) - x_6 \cdot j - x_7 \cdot j^{(1+x_8)}$$
(2)

Where the parameters $x_1,...,x_7$ and x_8 are given by

$$x_8 = (1 + p_{4i}^2) / (0.25 p_{4i})$$
(3)

$$x_{7} = \frac{(p_{4\nu} - p_{3\nu}) + (p_{2\nu} - p_{3\nu})((p_{4i} - p_{3i})/(p_{3i} - p_{2i}))}{-p_{4i}^{(1+x_{8})} + p_{3i}^{(1+x_{8})}((p_{4i} - p_{3i})/(p_{3i} - p_{2i}))}$$
(4)

$$x_6 = ((p_{2\nu} - p_{3\nu}) - x_7 p_{3i}^{(1+x_8)}) / (p_{3i} - p_{2i})$$
(5)

$$x_5 = (p_{2i} - p_{1i})/4 \tag{6}$$

$$x_4 = p_{1\nu} - p_{2\nu} - x_6 p_{2i} \tag{7}$$

$$x_{3} = 2p_{o2,ca}^{0} \left(\Delta V_{fc} \,/\, \Delta p_{o2,ca}\right) \tag{8}$$

$$x_2 = \Delta V_{fc} / \Delta T_{st} \tag{9}$$

$$x_1 = p_{1\nu} - x_3(0.5\ln(p_{o2,ca}^0) + \ln(p_{H2}^0))$$
(10)

where the current density *j* is given by

$$j = I_{st} / A_{fc} \tag{11}$$

where I_{st} is the stack current. p_{ki} and p_{kv} (k = 1,...,4) are the currents and voltage experimental points used to model the fuel cell and there values are presented in [8]. T_{st} and T_{st}^{0} are the fuel cell stack and the ambient temperature respectively. The stack power is given by

$$P_{st} = V_{st} I_{st}$$
(12)

Matlab/Simulink is used to simulate the performance of the fuel cell system under different load currents. Fig. 3 shows a comparison between the polarization curve of the model and the Ballard 1.2 kW Nexa fuel cell module [9]. Table I lists the basic operating parameters of the module.

Deremeter	Value
Parameter	value
Rated power	1 2 KW
Italed power	1.2 1.00
Operating voltage	22-50\/
oporating voltage	22 001
Voltage at rated power	26

Table I: Basic parameters of the fuel cell system [9].



Fig 3. Polarization curve of Ballard 1.2 KW Nexa module [9]

Fuel cell/Hydrogen sizing

A simplified procedure for determining the number of fuel cells needed to offset a wind turbine and the amount of hydrogen consumed has been used. Two 1.2 kW fuel cells are considered to generate the same peak power generated by the 2.4 kW wind turbine (2x1.2 kW=2.4 kW). The amount of hydrogen consumed by a fuel cell (in kWh) can be calculated as follows:

$$E_{H2}(t) = \frac{E_{Gen}(t)}{\eta_{inv}\eta_{fc}}$$
(13)

where $E_{Gen}(t)$ is the energy generated by the fuel cell at time t, η_{inv} is the efficiency of the inverter (0.95) and η_{fc} is the efficiency of the fuel cell system which depends on the

current drawn by the load. At standard conditions, 1 kg of hydrogen produces 33.3 kWh of energy [10]. This ratio is used to calculate the volume of hydrogen consumed.

Block diagrams of the wind system and the hydrogen/fuel cell system are depicted in Fig. 4 and Fig. 5 respectively.



Fig 4. Block diagram of wind energy system



Fig 5. Block diagrams of hydrogen/fuel cell system

RESULTS

The wind power has been calculated using the manufacturer's curve model of 2.4 KW wind turbine. Sample window of the power generated by the wind turbine is shown in Fig. 6 (Dotted line).



Fig. 6. Wind turbine power profile

From this figure, it can be seen that the wind power is highly fluctuating. To define the equivalent fuel cell/hydrogen system that is able to produce the same power generated by the wind turbine, the output power profile of the wind turbine is considered as a demand for the fuel cell/hydrogen system. However, Due to its slow dynamics, fuel cells system cannot supply highly fluctuating demand. For that reason, the one year hourly resolved wind power profile is averaged over 10 hours interval. The fuel cell system is considered to generate constant power during each 10 hours interval equal

to the calculated average. The new profile is called normalized power profile and it is shown in Fig. 6 (solid line).

The amount of hydrogen in kWh consumed by the fuel cell system over one year is depicted in Fig. 7. The figure shows the hydrogen consumed by two fuel cells. The total annual amount of hydrogen is 253Kg.



Fig. 7. Hydrogen consumption of the fuel cells/hydrogen system.

To compare the performance of the wind energy system and fuel cell energy system, the conversion efficiency of each system is calculated by dividing the actual power generated and the maximum available power. Results show that wind energy system is less efficient than fuel cell system. Table III shows a comparison between the performances of both systems.

 Table III: Comparison between the performance of the wind power system and fuel
 cells/hydrogen system.

	Fuel cell	Wind turbine
Rated power	1.2 KW	2.4 KW
Number of components	2	1
Efficiency	0.4039	0.3246
Hydrogen consumption	253 Kg/year	Not applicable

CONCLUSIONS

In this paper, fuel cell/hydrogen energy system is sized to offset the power generated by wind energy system. Actual wind speed profile for one year is fed into wind turbine model based on the manufacturer's power curve to simulate the annual wind power yield. The resultant power profile is used to determine the number of fuel cell devices and the amount of hydrogen needed. Results show that fuel cell/hydrogen energy system has higher energy conversion efficiency compared to wind energy system.

REFERENCES

[1] M. Elhadidy and S. Shaahid, "Optimal sizing of battery storage for hybrid (wind+ diesel) power systems," *Renewable Energy,* vol. 18, pp. 77-86, 1999.

[2] B. S. Borowy and Z. M. Salameh, "Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system," *Energy Conversion, IEEE Transactions on,* vol. 11, pp. 367-375, 1996.

[3] D. B. Nelson, *et al.*, "Unit sizing of stand-alone hybrid wind/PV/fuel cell power generation systems," presented at the Power Engineering Society General Meeting, 2005. IEEE, Montana, USA, 2005.

[4] BOM. (20 July). *Climate Glossary*. Available: http://www.bom.gov.au/climate/glossary/seasons.shtml

[5] D. Chiras, *Wind power basics*. New York, NY, USA New Society Publishers, 2010.

[6] Energy matters. (8th October 2012). *Southwest Windpower Skystream 2.4kW Residential Wind Turbine*. Available: http://www.energymatters.com.au/southwest-windpower-skystream-24kw-residential-wind-turbine-p-439.html

[7] C. A. Ramos-Paja, *et al.*, "Minimum fuel consumption strategy for PEM fuel cells," *Industrial Electronics, IEEE Transactions on,* vol. 56, pp. 685-696, 2009.

[8] A. J. del Real, *et al.*, "Development and experimental validation of a PEM fuel cell dynamic model," *Journal of power sources*, vol. 173, pp. 310-324, 2007.

[9] Ballard Power Systems Inc., "Nexa[™] Power Module User's Manual MAN5100078," ed, 2003. [10] Committee on Alternatives Strategies for Future Hydrogen Production and Use, *Hydrogen Economy: Opportunities, Costs, Barriers, and R&D Needs*. Washington, DC, USA: National Academies Press, 2003.






Figure 2: The fit of measured and predicted load demand. Predictions made using RBF-NN with LTP=10 hours. The training data are load data only.