Optimization of Renewable Hybrid Energy Systems – A multi-objective approach

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Abstract

For a successful transition to a renewable energy economy, optimisation of renewable energy systems must evolve to take into account not only technical and/or economic objectives, but also environmental and socio-political objectives. A Normalised Weighted Constrained Multi-Objective (NWC MO) meta-heuristic optimisation algorithm has been proposed for achieving a compromise between mutually conflicting technical, economic, environmental and socio-political objectives, in order to simulate and optimise a renewable energy system of any configuration. In this paper, an optimisation methodology based on these four classes of objective is presented. The methodology was implemented using Particle Swarm Optimisation and tested against data from the literature. In the Case Study the original results could be reproduced, but the newly-implemented algorithm was further able to find a more optimal design solution under the same constraints. The influence of additional quantified socio-political inputs was explored.

Keywords: design methodology, economic - technical - environmental - socio-political objective, optimisation.

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Nomenclature

A	Constants for fuel consumption (l/kW)	i	Nominal interest (%)
B	Constants for fuel consumption (l/kW)	Init	Initial cost (\$)
AD	Autonomous days	INV	Inverter
AMT	Local meridian time	k_t	Temperature loss factor (1/°C)
B_{AC}	Battery capacity (Ahr)	kW	Kilo watt
B_{RC}	Rated capacity of battery (Ahr)	kWh	Kilo watt hours
C_d	Capital cost (\$)	LCOE	Levelized cost of energy (\$/kWh)
CFOE	Carbon footprint of electricity ($kgCO_{2eq}$)	LMT	Local Meridian Time
C_{repd}	Repair costs (\$)	LMST	Local Mean Solar Time
C_{fuel}	Cost of fuel (\$)	LOD	Longitude
$C_{O\&Md}$	Cost of operations and maintenance for a device (\$)	LPS	Loss of power supply
CO_{2em}	CO2 emissions from running diesel generator (CO2eq)	LPSP	Loss of power supply probability
CO_{2eq}	Carbon dioxide equivalent	LSMT	Local Standard Meridian Time
C_{repd}	Cost of replacement of device (\$)	n	System life time (years)
CRF	Capital recovery factor	NPV	Net present value
D	device	NWCMO	Normalise weighted constrained multi objective
DG	Diesel generator	OM	Operation and maintenance
DOD	Depth of discharge (%)	P_{bat}	Energy of battery (kWh)
DOD_{max}	Max DOD (%)	Op_{hours}	Operational hours of diesel generator.
Ec	Economic	Pbest	Particle best
Ec_{obj}	Economic objective	P_{ch}	Charge energy (kWh)
EF	Emission factor (kg/litre)	P_d	Power of device (kW)
EL	Electrical load (kW)	P_{ele}	Electrolyser consumption (kW)
Env	Environmental	P_{fc}	Power of fuel cell (kW)
Env_{obj}	Environmental objective	P_{gen}	Generated power (kW)
EOt	End of Time	PEM	Proton exchange membrane
fc_{H_2}	Fuel cell hydrogen consumption (kg/hr)	PEMFC	Proton exchange membrane fuel cell
$fc_{P_{max\,eff}}$	Fuel cell max efficiency (%)	P_{diesel}	Output power from diesel generator (kW)
fc_{pnom}	Nominal fuel cell output power (kW)	P_{ele}	Electrolyser electrical consumption (kW)
fc_p	Fuel cell output power (kW)	P_{gen}	Generated power (kW)
$fuel_{cons(t)}$	Fuel consumption of diesel generator litre)	$P_{gen,diesel}$	Power from diesel generator (kW)
fc_{H_2}	Fuel cell hydrogen consumption (kg/h)	PMI	Power management interface
$fuel_{cons}$	Fuel consumption diesel generator (l)	Pr	Rated power (kW)
G	Solar radiation (W/m2)	P_{RE}	Generated power from renewable energy sources (kW)
G_{ref}	Reference solar radiation (W/m2)	PSO	Particle swarm optimization
gbest	Global best	PV	Photovoltaic
GHG	Greenhouse gas	pV_A	Area of pv system (m2)
GMT	Greenwich Mean Time	pV_{cap}	Capacity of pv system (kW)
GW	Gigawatt	$pV_{cap\,mod}$	Capacity of pv module (kW)
H	Height (m)	pV_{life}	Life of pv system (years)
H_2	Hydrogen	$pV_{invlife}$	Life of pv inverter (years)
H_{2level}	Tank of hydrogen tank	q	Fuel consumption (l/hr)
$H_{2min-level}$	Minimum hydrogen tank level	Q_{H_2}	Mass flow of hydrogen (kg/hr)
$H_{2max-level}$	Maximum hydrogen tank level	Q_{n-H_2}	Nominal mass flow of hydrogen (kg/hr)
HRES	Hybrid renewable energy systems	R_B	Ratio between global and tilted solar energy

R_D	Ratio between diffused global and titled solar energy	$\mathcal{E}_{env}$	Environmental constraint
RF	Renewable factor (%)	$\mathcal{E}_{gen}$	CO2 emissions from generator ($kgCO_{2eq}$)
RES	Renewable energy system	$\mathcal{E}_{pv aux}$	CO2 emissions from auxiliary PV devices ($kgCO_{2eq}$)
R_R	Ratio of reflected solar energy on a tilted surface	$\mathcal{E}_{pv}$	CO2 emissions from PV ($kgCO_{2eq}$)
SF	Safety factor	$\mathcal{E}_{pv inv}$	CO2 emissions from PV inverter ($kgCO_{2eq}$)
SOC	State of charge (%)	$\mathcal{E}_{pv mod}$	CO2 emissions from PV modules ($kgCO_{2eq}$)
Socio	Socio-political	$\mathcal{E}_{pv str}$	CO2 emissions from PV structure ($kgCO_{2eq}$)
$Socio_{obj}$	Socio-political objective	$\mathcal{E}_{pv wire}$	CO2 emissions from PV wire ($kgCO_{2eq}$)
SOC_{max}	Maximum level of battery charge (%)	$\mathcal{E}_{socio}$	Socio-political constraint (1)
SOC_{min}	Minimum level of battery charge (%)	$\mathcal{E}_{sys}$	Total system emission ($kgCO_{2eq}$)
$SOC(t)$	State of charge	$\mathcal{E}_{tech}$	Technical constraint (%)
T_{amb}	Ambient temperature (°C)	η_b	Battery efficiency (%)
T_{cf}	Temperature correction factor (°C)	η_{ele}	Efficiency of electrolyser (%)
Tec	Technical	$\eta_{H_2 tank}$	Efficiency of the hydrogen tank (%)
$Tech_{obj}$	Technical objective	η_{inv}	Inverter efficiency (%)
TEL	Total energy lost (kWh)	σ	Self discharge rate (%)
TPV	Total present value (\$)	$\gamma_{pv aux}$	Emissions from pv auxiliary devices ($kgCO_{2eq}$)
Tref	Reference temperature (°C)	$\gamma_{pv inv}$	Emissions from pv inverter ($kgCO_{2eq}$)
V	Velocity (m/s)	$\gamma_{pv mod}$	Emissions from PV module ($kgCO_{2eq}$)
V_B	Battery voltage (V)	$\gamma_{pv str}$	Emissions from PV structure ($kgCO_{2eq}$)
$v_{cut in}$	Cut in velocity (m/s)	$\gamma_{pv wire}$	Emissions from PV wires ($kgCO_{2eq}$)
$v_{cut out}$	Cut out velocity (m/s)		
v_{max}	Max velocity		
v_r	Rated velocity (m/s)		
W	Weighted		
A	Friction coefficient		
α_{fc}	Coefficients of the electrical consumption curve (kg/kWh)		
α_{ele}	Coefficients of the electrical consumption curve (kg/kWh)		
β_{ele}	Coefficients of the electrical consumption curve (kg/kWh)		
$\mathcal{E}_{bat}$	CO2 emissions from battery ($kgCO_{2eq}$)		
$\mathcal{E}_{bat inv}$	CO2 emissions from battery inverter ($kgCO_{2eq}$)		
$\mathcal{E}_{ec}$	Economic constraint		

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1 Advancing beyond techno-economic assessment

A detailed literature review by Eriksson and Gray [1] of the field of optimisation of renewable energy systems identified a research gap in multi-objective optimisation of energy systems for sustainable energy delivery.

This paper elaborates and applies the idea, discussed by Eriksson and Gray [1], of a four-dimensional multi-objective meta-heuristic simulation and optimisation model which simultaneously takes into account technical, economic, environmental and socio-political objectives, using weighting factors to tailor the design goals to the circumstances and conditions under which the energy system is built.

Decisions about energy systems are made based on cost. Previously, “cost” almost exclusively meant the monetary cost to the stakeholders to build and profitably operate the energy system. Environmental and social costs generally were not factored into the calculations. This is the main reason why very large renewable energy systems are now needed urgently. Yet despite the imperative to reduce carbon-dioxide and other emissions, new renewables-based energy systems continue to be costed on the same techno-economic basis as those based on fossil fuels, and are expected to be competitive in monetary terms. A true comparison requires that both the proposed renewables-based system and the alternative be costed on a level playing field, which must include all the monetary and other costs paid immediately or eventually. While this has long been recognised in principle, in practice comprehensive modelling that includes factors other than techno-economic is still very rare. The urgency to implement this novel approach is underlined by the recent quantification of the effects of pollution on human health [2].

To minimise the monetary or other cost of energy production whilst upholding reliability of supply already constitutes a complex multi-objective optimisation problem with

conflicting objectives. Even considering only monetary cost and performance, classical methods of optimisation have struggled with the complexity of the problem of optimally designing a hybrid renewable energy system [1]. Adding environmental and socio-political dimensions significantly compounds the problem. Applied to new energy systems, an approach that accounts for not just technical and economic but also environmental and socio-political factors will lend credibility to the design as a defensible compromise between conflicting objectives. Examples of the latter factor are public acceptance of land-based wind farms and possible negative perceptions of hydrogen safety. The challenge is to find a practicable approach to performing the optimisation.

In [1], the authors surveyed methodologies and software used in optimisation studies of hydrogen-based energy systems. They concluded that there was a need for a more flexible approach to shaping design objectives additional to cost and technical performance. The available software packages were found to lack capability in modelling hydrogen-based system components and that no software package incorporated factors beyond cost, performance and (sometimes) environmental footprint. Bio-inspired optimisation algorithms were identified as being well suited to solve the complex problem of optimising a multi-component energy system in which hydrogen is one of the energy vectors. A four-dimensional objective function was proposed with weightings applied to monetary cost, technical performance, environmental footprint and socio-political factors.

A new four-dimensional multi-objective meta-heuristic algorithm is implemented and demonstrated in this paper. To construct the simulation and optimisation model, a new methodology developed around the Particle Swarm Optimisation algorithm is introduced and tested against existing studies from the literature, by first reproducing those studies, then searching for a more nearly optimal system configuration. In all cases, the new optimisation algorithm quickly finds a better configuration that still satisfies the original constraints. In

order to incorporate socio-political factors, a list of quantifiable factors is first proposed. Then the influences of some simple hypothetical socio-political factors on the studied systems are explored and the effects on the system performance and monetary cost are demonstrated.

The remainder of the paper is organised as follows: Section 2 gives an overview of the optimisation approach taken; Section 3 outlines the four classes of objectives, includes suggested quantifiable socio-political factors and introduces the Normalised Constrained Weighted Multi-Objective; Section 4 discusses the search function algorithm; Section 5 outlines the mathematical models of individual system components within the optimisation model; Section 6 details a Case Study used to verify the optimisation model; Section 7 contains a summary and conclusions.

2 Optimization overview

Based on the critical review of methodologies and software by Eriksson and Gray [1], a flexible optimisation and simulation model has been adopted within which a system can be optimised, either based on a search for best system devices using user constraints and/or using a minimised Normalised Weighted Constrained Multi-Objective (NWCMO) meta-heuristic function. Figure 1 illustrates the design method used to put these ideas into practice, and the steps taken when evaluating a design with respect to the four sets of objectives. The type of energy system considered generates electricity from renewables, but the principles and approach are general. Inputs to the model are PSO parameters, technical, economic, environmental and socio-political parameter constraints, normalised weightings for the four objective classes, simulation period, device system configuration, weather data and load data. A key requirement is to quantify socio-political factors so that they become numerical inputs to the optimisation task.

Figure 1: Optimisation algorithm

3 Objectives

The various well-known approaches to quantifying technical and economic objectives were surveyed in [1], along with less-often used environmental objectives. The following section briefly outlines the methods adopted in this new optimisation model to evaluate technical, economic and environmental objectives. More details will be found in the recent review and references therein. A social and political acceptance index is introduced here as a quantifiable socio-political objective.

3.1 Technical objective

Analysis of the reliability of supply plays a vital role when incorporating renewable energy in energy systems, owing to the fundamental intermittency of renewable energy

sources. The technical objective adopted in this paper is the well-known Loss of Power Supply Probability (LPSP). *LPSP* is defined as the ratio of the summed energy deficits to the total load energy demand over a selected period, ranging from 0 (load always satisfied) to 1 (load never satisfied) [3]. The aim is usually for *LPSP* to be as close to 0 as possible.

$$LPSP = \frac{\sum_{t=1}^T LPS(t)}{\sum_{t=1}^T E_L(t)} [\%] \quad (1)$$

where E_L is the load [kWh] and LPS is the summed energy deficit [kWh]. LPS varies depending on the system components and naturally decreases when more energy generating sources are present in the system.

A Safety Factor (SF) may be applied to express a desired load safety percentage margin, or as an alternative to re-analysing the design based on data for unlikely but severe weather, with the outcome of a more robust energy system, inevitably at higher cost.

3.2 Economic objective

The economic objectives evaluated in this paper are Levelized Cost of Energy (LCOE) and Net Present Value (NPV). LCOE is an adopted economic criterion, which quantifies the economic feasibility of an energy system as a system's cost over lifetime divided by its lifetime energy production. The present value of the total costs of the system is calculated over an assumed lifetime. For a hybrid energy system, the present value of costs can be composed of the initial cost, the present value of maintenance cost, the present value of replacement cost and the Capital Recover Factor (CRF) of the hybrid energy system. LCOE is calculated as [4]

$$LCOE = \frac{TPV}{E_L} CRF \text{ [$/kWh]} \quad (2)$$

where E_L is the total load over the simulation period [kWh]. The Total Present Value (TPV) of the system [\$] varies according to the components that make up the system:

$$TPV = \sum_{d=1}^k C_d \text{ [$]} \quad (3)$$

where d represents the device to be optimised and C_d consists of $Init_d$ the initialisation [\$] costs and $C_{O\&M_d}$, the operation and maintenance [\$] costs:

$$C_d = Init_d + C_{O\&M_d} \text{ [$]} \quad (4)$$

In Eqn (2) CRF calculates the present value of the system components for a given time period, taking into consideration the interest rate:

$$CRF = \frac{i(1+i)^\eta}{(1+i)^\eta - 1} \quad (5)$$

where i the nominal interest rate [%] and η is the system life [years].

Net Present Value (NPV) can be expressed as a sum over devices (d) [5]:

$$NPV = \sum_{d=1}^k \left[C_d + C_{O\&M_d} CRF + C_{repd} \frac{1}{(1+i)^{L_d n_d}} \right] \times P_d + C_{fuel} \times Op_{hours} \times fuel_{cons} CRF \text{ [$]} \quad (6)$$

$C_{O\&M_d}$ is repair cost, L_d is the lifetime of the specific device, n_d represents the number of replacements needed to occur in the lifetime of the project (typically set to 25 years). P_d is the power of the specific device in kW. $fuel_{cons}$ only apply if system has a diesel generator, where C_{fuel} is the cost of fuel to run the diesel generator, Op_{hours} is the hours of operation and $fuel_{cons}$ is its fuel consumption in litre/hour.

Finally, the economic model used here takes into account direct or indirect (taxation) government subsidies.

3.3 Environmental objective

The environmental objective evaluated in this paper is Carbon Footprint of Electricity (CFOE), which incorporates direct CO₂ emissions from any diesel generators or similar, ε_{gen} . An environmental objective could imply the calculation of the generated CO₂ emissions associated with manufacturing, shipping, operating and maintaining the system as well as final waste disposal. A cradle-to-grave approach for CFOE enables the energy system to be considered based on the greenhouse gas emissions quantified in equivalent CO₂ mass per kWh of produced energy (kgCO_{2eq}) throughout the system's lifetime [6-9]. The elements of the environmental impact analysis are illustrated in Figure 2.

Figure 2: Environmental objective

The CFOE is measured in kgCO_{2eq}/kWh and can be expressed as follows:

$$CFOE = \frac{\varepsilon_{sys}}{E_L} [\text{kgCO}_{2eq}/\text{kWh}] \quad (7)$$

where ε_{sys} is the total emissions produced by the system during manufacturing and operation [kgCO_{2eq}] and E_L is the total simulated load [kWh]. The total emissions from an energy system ε_{sys} consisting of PV, batteries, inverter, generator, interconnects and so on is

$$\varepsilon_{sys} = \varepsilon_{pv} + \varepsilon_{bat} + \varepsilon_{batinv} + \varepsilon_{gen} + \varepsilon_{syswires} \dots \quad (8)$$

where ε_{pv} , ε_{bat} , ε_{batinv} , ε_{gen} and $\varepsilon_{syswires}$ are the emissions associated with the PV system, battery and battery inverters, diesel generator and associated interconnects and system wires respectively.

Within this total, each component of emissions can be further broken down according to its component. For example, the total emissions in kgCO_{2eq} from the PV component can be expressed as follows:

$$\varepsilon_{pv} = \varepsilon_{pvmod} + \varepsilon_{pvstr} + \varepsilon_{pvinv} + \varepsilon_{pvwir} + \varepsilon_{pvau} [\text{kgCO}_{2eq}] \quad (9)$$

where ε_{pvmod} , ε_{pvinv} , ε_{pvstr} , ε_{pvwire} and ε_{pvau} are the emissions associated with the PV modules, PV inverter, PV structures, electrical wires in the PV system and auxiliary devices such as circuit breakers and switchboards respectively. All remaining system devices are evaluated using the same principle.

Where the emissions come mainly from operating a diesel or other generator, a simplified environmental objective may be calculated from the operating fuel emissions from the generator, ignoring other emissions, as follows [5, 8]:

$$\varepsilon_{gen} = \sum_1^T \text{fuel}_{cons(t)} EF [\text{kgCO}_{2eq}] \quad (10)$$

where the emission factor (EF) [kg/litre] depends on the type of fuel as well as the engine characteristics (typically 2.4–2.8 kg/litre) [10] and $\text{fuel}_{cons(t)}$ is the fuel consumption of the

diesel generator. The total emissions from a diesel generator system are calculated in a similar fashion to the above example for the PV component with the in-operation diesel generator emissions added to the final emissions.

3.4 Socio-political objective

Incorporating socio-political criteria is obviously less straightforward and less certain than an analysis based only on quantitative technical, economic objectives and/or environmental objectives, but very important because real projects are subject to such factors. Numerical quantification is necessary in order to adopt an algorithmic approach to optimization. Hence, a socio-political index is proposed as an example of an adaptive, multi-input evaluation aid to analysing an energy system from a socio-political perspective. The concept uses both qualitative and quantitative factors to measure a socio-political objective through an index-based approach to judge all parameters on the same basis. The outcome is a numeric value, which in this example of the methodology represents the expected public satisfaction with/acceptance of a proposed energy system.

In order to analyse quantitative figures, each factor is assigned a numerical value between one and five (five for worst, one for best) proportional to its impact on the renewable energy system project.

Each parameter is assigned a certain weight from zero to 100 percent (zero for no impact, 100 for full impact) based on its relative importance specific to the current project being analysed. The weighted sum of all the parameters constitutes the socio-political numerical objective value. The NWCMO meta-heuristic function seeks to minimise the socio-political objective along with the more familiar objectives.

The socio-political index proposed is inherently semi-quantitative, as there is no standard approach to assign weights to the parameters. This reflects the actual nature of qualitative parameters. However, if a participatory approach with stakeholders, decision

makers, political representatives and the local community is used in interpreting parameters and weights, the usefulness of the socio-political index improves, as it is then tailored to that specific project. Parameters can be varied depending on local conditions, but this also reduces the standardization of the method to some degree. The numerical values of interpreted parameters and weights should be accumulated over time so that comparisons of similar projects and known indicators can be taken advantage of. A list of possible parameters is presented below which may be taken into consideration while devising a socio-political index, notated *Socio*.

Table 1: Socio-political objective

Parameter	Parameter description	Parameter factor value scale 5 (lowest)-1 (highest)	
Aesthetics	Public acceptance to visual appearance, shadow flicker and noise disturbance etc.	Unacceptable	Acceptable
Employment	Employment opportunities in number of employees		
Perceived hazard	Potential hazard risk	High	Low
Land requirement and acquisition	Ability to acquire land for the project and level of public resistance	Unacceptable	Acceptable
Perceived local environmental impact	Local identified environmental Impact such as eco-system disturbance	High	Low
Local ownership	Degree of local ownership	(%)	
Local skills availability	Availability of local skills	Unavailable	Available
Local resource availability	Availability of local Resources	Unavailable	Available
Renewable factor RF	Penalise reliance on non-renewable energy.	(%)	
Perceived service ability	Level of improved service ability, i.e. improved availability of social electricity services such as street lighting, telecommunications etc.	Low	High
Total	Socio:		

A renewables factor RF may be introduced for the purpose of penalising non-renewable energy. An example of the RF used in a system incorporating a diesel generator is

$$RF = \left(1 - \frac{\sum_1^T P_{gen_{diesel}}}{\sum_1^T P_{RE}} \right) [\%] \quad (11)$$

where $\sum_1^T P_{gen_{diesel}}$ (kWh) is the sum of the total output of fuel consumption from a diesel generator over the simulation period and $\sum P_{RE}$ (kWh) is the sum of the total renewable energy mix output over the simulation period.

3.5 Normalised Weighted Constrained Multi-Objective

Many real world problems are concerned with so-called multi-objectives where a solution is sought as the best possible compromise. Optimisation can be defined as the process of finding conditions that give the minimum value of a function which numerically expresses the value of the optimized system to the stakeholders in that system.

An optimisation problem can generally be stated as follows:

$$\text{Find } X = \begin{Bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{Bmatrix} \text{ which minimizes } f(X) \quad (12)$$

subject to the constraints

$$g_j(x) \leq 0, j = 1, 2, \dots, m \quad (13)$$

where $f(x)$ is the objective function, x is an n -dimensional design vector and $g_j(x)$ are set out constraints that may or may not be related [11]. There is no single best method for solving all such optimization problems efficiently, and many differing mathematical optimization-

programming techniques are available in the context of renewable energy systems depending on the nature of the optimisation problem .

To solve the optimization problem involving multiple objective functions, a minimisation fitness function is adopted which results in an overall optimisation solution, as follows:

If $f_{1_{NORM}}(x) \cdots f_{o_{NORM}}(x)$ are the normalised objective functions corresponding to the proposed number sets of objectives, a new overall Normalised Constrained Weighted Multi-Objective (NCWMO) function can be established such that

$$\min f_{NCWMO}(x) = \sum_{k=1}^p w_k f_{NCWMO}(x) \quad (14)$$

where f_{NCWMO} is the normalised objective, w_i are weightings such that $\sum_{i=1}^k w_i = 1$ whose values indicate the relative weight given to each objective function; in other words a quantitative implementation of the scheme proposed by Eriksson and Gray [1].

3.5.1 Global energy audit figure

At the end of each optimisation, it is appropriate to conduct a “reality check”, which constitutes a bottom-line assessment of whether the optimisation is sensible. In the example described here, the excess renewable energy potentially generated but not used by a renewable system is assessed. This could be a major factor in a system not going ahead due to oversizing and its consequences, such as escalating cost, problems with land acquisition, unnecessary environmental emissions and so on. The notional available renewable energy under prevailing conditions can be seen as surplus energy. Whilst somewhat misleading, the term commonly used in literature for this concept is Total Energy Lost (TEL). Extra power generation from a renewable energy source may be minimised by imposing a threshold value which must not be exceeded throughout the simulation . TEL may be expressed as:

$$TEL = \begin{cases} \sum_{t=1}^T P_{gen}(t) - E_L(t), & E_L(t) < P_{gen}(t) \text{ [kWh]} \\ 0 \end{cases} \quad (15)$$

where P_{gen} is the generated energy [kWh], E_L is the load [kWh].

Whilst TEL does not necessarily equal the surplus energy from the system when there are storage devices present in the system, it still serves as a useful reference point for benchmarking systems against each other.

3.5.2 Constraints

Constraints are restrictions imposed on the available resources and environment (e.g. time restriction, physical limitation), and are defined as dependencies among the parameters and decision variables that are involved in the problem. A constraint may be of inequality or equality type and restricts a variable to be between a lower and upper bound in a decision space.

In the present context, each objective should be less than its corresponding constraint:

$$tech_{obj} \leq \epsilon_{tech} \quad (16)$$

$$ec_{obj} \leq \epsilon_{ec} \quad (17)$$

$$env_{obj} \leq \epsilon_{env} \quad (18)$$

$$socio_{obj} \leq \epsilon_{socio} \quad (19)$$

where ϵ_{tech} , ϵ_{ec} , ϵ_{env} , ϵ_{socio} are respectively the technical, economic, environmental and socio-political constraints corresponding to the four objectives. These constraints may be set by the user for a particular objective during the initial model configuration.

Finally, there are non-negativity constraints, energy flow and lower and upper limits for decision variables. These specific constraints are applied to particular components to ensure

that the outputs of the optimisation are physically meaningful and are initialised at the start of the optimisation. For example, the constraints for battery charging/discharging and hydrogen storage/retrieval respectively can be expressed as:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (20)$$

$$H_{2min-level} \leq H_{2level}(t) \leq H_{2max-level} \quad (21)$$

4 Optimisation algorithms

Optimisation approaches and algorithms were recently reviewed in Ref. [1], where it was found that Particle Swarm Optimisation (PSO) is a fast, accurate and relatively easy-to-implement algorithm suitable for solving multi objective search functions. A modified PSO algorithm was therefore implemented for this work, to search for a configuration of devices in the energy system. PSO is similar to other evolutionary algorithms, in that a system is initialised with a population of random solutions in a search space, then evaluated against a fitness function. Each solution is a so-called particle, with a velocity which is updated to optimise its position in the search space. Every particle is optimised by following a *pbest* value, which is the best fitness value the particle has achieved so far, and a *gbest* value, which is the best global value in the search space. A particle's velocity is dependent on how far it is from the target as well as being constrained by minimum and maximum boundaries.

The pseudo code below outlines the main function of the PSO algorithm which runs until the maximum iteration number or a set satisfied constraint is fulfilled.

```

While max iterations or minimum error criteria not met
  For each particle
    Initialise particle
  End
  For each particle
    Calculate fitness value
    If the fitness value is better than historic pbest best value
      Set current fitness value to new pbest
  End

```

```

395     If pbest is better than historic gbest best value of all the particles
396         Set pbest to new gbest
397     End
398
399     Calculate particle velocity
400     Update particle position
401     End
402 End
403
404     Each particle has two variables, its current position  $\mathbf{x}_{ij}(\mathbf{t})$  and its velocity  $\mathbf{v}_{ij}(\mathbf{t})$  with

```

the *pbest* value stored in $\mathbf{p}_{ij}(\mathbf{t})$, while $\mathbf{g}_j(\mathbf{t})$ denotes the best global particle. Parameters required to be tuned and initialised at start-up for a PSO search function include the number of particles, the maximum adjustment a particle can undergo during one iteration *vmax*, learning factors, the stop condition; the maximum number of iterations or convergence requirement and inertia weight all of which affect the velocity of the particle.

The particle velocity and position are updated as follows [12]:

$$\mathbf{v}_{ij}(\mathbf{t} + 1) = \omega \mathbf{v}_{ij}(\mathbf{t}) + r_1 c_1 (\mathbf{p}_{ij}(\mathbf{t}) - \mathbf{x}_{ij}(\mathbf{t})) + r_2 c_2 (\mathbf{g}_j(\mathbf{t}) - \mathbf{x}_{ij}(\mathbf{t})) \quad (22)$$

$$\mathbf{x}_{ij}(\mathbf{t} + 1) = \mathbf{x}_{ij}(\mathbf{t}) + \mathbf{v}_{ij}(\mathbf{t} + 1) \quad (23)$$

In Eqn (22) $\mathbf{v}_{ij}(\mathbf{t})$ is the inertia velocity, $\omega \mathbf{v}_{ij}(\mathbf{t})$ is the inertia term and ω is the inertia coefficient which ensures that there is a smooth transition between previous and current velocities.

The term $r_1 c_1 (\mathbf{p}_{ij}(\mathbf{t}) - \mathbf{x}_{ij}(\mathbf{t}))$ in Eqn (22) is known as the cognitive component and $r_2 c_2 (\mathbf{g}_j(\mathbf{t}) - \mathbf{x}_{ij}(\mathbf{t}))$ is known as the social component, where c_1 is the cognitive learning factor guides particles towards the optimum value, and the social learning factor c_2 represents the attraction toward other particles. r_1 and r_2 are randomly generated numbers within interval (0, 1). Clerc and Kennedy proposed a constriction factor to restrict the swarm in a multi-dimensional space as follows [12]:

$$\mathbf{v}_{ij}(\mathbf{t}+1) = \chi \left(\omega \mathbf{v}_{ij}(\mathbf{t}) + r_1 c_1 (\mathbf{p}_{ij}(\mathbf{t}) - \mathbf{x}_i(\mathbf{t})) + r_2 c_2 (\mathbf{g}_j(\mathbf{t}) - \mathbf{x}_{ij}(\mathbf{t})) \right) \quad (24)$$

where χ is the constriction coefficient and is defined by

$$\chi = \frac{2k}{2 - \phi - \sqrt{\phi^2 - 4\phi}} \quad (25)$$

where $\phi = \phi_1 + \phi_2 \geq 4$, typically $0 \leq k \leq 1$, $\phi_1 = 2.05$ and $\phi_2 = 2.05$ [12]. An optimal setting of the parameters depends on the current optimisation problem. As demonstrated in the simulations in section 6, suitable values for setting the main parameters of PSO algorithm ω , c_1 , c_2 and the swarm size are:

$$\omega = \chi \quad (26)$$

$$c_1 = \chi \phi_1 \quad (27)$$

$$c_2 = \chi \phi_2 \quad (28)$$

The simulation model is run for the whole simulation period to evaluate the performance of each particle. The simulation model calculates the objective functions discussed in section 3. Particles in the swarm size are evaluated against the NWCMO fitness function until the stopping criterion is met and the best of all evaluated solutions is presented.

To speed up the PSO algorithm when running through a large search space, a historical look-up table is kept so that previously calculated values do not have to be recalculated.

5 Simulation models

A particle represents a certain configuration of a hybrid renewable energy system for a simulation period (in this study set to one year with hourly time interval analysis) of electricity demand and weather data (typically solar radiation, wind speed and ambient temperature). The particle represents any combination of device sizes for PV, wind, battery,

generator, electrolyzers, fuel cells and hydrogen tanks that are simulated and optimised to test the viability of the system.

Many mathematical representations of components including PV, wind, generators, battery, fuel cells, electrolyzers, hydrogen storage, inverters and auxiliary devices have been published. Here a modular architecture has been adopted, using simplified component models for demonstration purposes. It is appropriate to think of the various mathematical models as black boxes so they can easily be interchanged with more sophisticated models to suit the goals of the analysis. The mathematical models implemented in the case studies reported in §6 are described briefly below.

5.1 PV model

Various simplified electrical and thermal mathematical models exist describing PV behaviour under external influences from solar irradiance and temperature.

A model of the solar radiation received by a tilted solar collector, described in detail by Khatib [13] was used. Briefly, the received radiation $G_{T,\beta}$ on a surface at angle β to the horizontal consists of three components: direct beam G_B , diffuse solar radiation G_D and reflected solar radiation $G_R = G_T \rho R_R$, such that

$$G_{T,\beta} = G_B R_B + G_D R_D + G_T \rho R_R \quad (29)$$

where R_B is the ratio between global solar energy on a horizontal surface and global solar energy on a tilted surface, R_D is the ratio between diffuse solar energy on a horizontal surface and diffuse solar energy on a tilted surface, R_R is the ratio of reflected solar energy on a tilted surface and ρ is the ground albedo factor. If only global irradiance data are available, the other contributions may be estimated based on a model of transmission and scattering by the atmosphere.

The altitude angle is the angular height of the sun measured from the horizontal and is expressed as follows:

$$\sin \alpha = \sin L \sin \delta + \cos L \cos \delta \cos \omega \quad (30)$$

Where L is the latitude of the location, δ is the angle of declination and ω is the hour angle. The angle of declination is the angle between the earth-sun vector and the equatorial plane and is calculated as follows:

$$\delta = 23.44 \sin \left[360 \left(\frac{d - 80}{365.25} \right) \right] \quad (31)$$

The hour angle ω is the angular displacement of the sun from the local point and is given by:

$$\omega = 15^\circ (AST - 12h) \quad (32)$$

AST is the true apparent or true solar time and is calculated by the daily apparent motion of the observed sun and is calculated as follows:

$$AST = LMT + EoT \pm 4 / (LSMT - LOD) \quad (33)$$

Where AMT is the local meridian time, LOD is the longitude, LSMT is the local standard meridian time and EoT is the equation of time. The LMST is a reference meridian and is given by :

$$LMST = 15^\circ T_{GMT} \quad (34)$$

EoT is the difference between the apparent and mean solar times, taken at a given longitude and is expressed as:

$$EoT = 9.87 \sin(2B) - 7.53 \cos B - 1.5 \sin B \quad (35)$$

$$B = \frac{2\pi}{365}(n-81) \quad (36)$$

Where n is the day number defined as the number of days elapsed in a given year up to a particular date.

The azimuth angle is an angular displacement of the sun reference from the source axis and can be calculated as follows:

$$\sin \theta = \frac{\cos \delta \sin \omega}{\cos \alpha} \quad (37)$$

Direct solar radiation $G_{B,norm}$ reaching the earth can be expressed as:

$$G_{B,norm} = A e^{\frac{-K}{\sin \alpha}} \quad (38)$$

Where A is an extraterrestrial flux and K is dimensionless factor.

$$A = 1160 + 75 \sin \left[\frac{360}{365}(N-275) \right] \quad (39)$$

$$K = 0.174 + 0.0035 \sin \left[\frac{360}{365}(N-100) \right] \quad (40)$$

Direct solar radiation on a horizontal surface G_B can be expressed as:

$$G_B = G_{B,norm} \sin \alpha \quad (41)$$

Diffuse solar radiation on a horizontal surface G_D can be calculated as follows:

$$G_D = 0.095 + 0.04 \sin \left[\frac{360}{365}(N-100) G_{b,norm} \right] \quad (42)$$

The coefficient R_b is most commonly represented as:

$$R_B = \frac{\cos(L - \beta) \cos \delta \sin \omega_{ss} + \omega_{ss} \sin(L - \beta) \sin \delta}{\cos L \cos \delta \sin \omega_{ss} + \omega_{ss} \sin L \sin \delta} \quad (43)$$

The coefficient R_R is given by the following equation:

$$R_R = \frac{1 - \cos \beta}{2} \quad (44)$$

The coefficient R_D is given by the following equation:

$$R_D = \frac{1 + \cos \beta}{2} \quad (45)$$

A detailed electrical model is usually based on the well-known Schottky diode equation for a single solar cell. At the array level, it is reasonable to assume that maximum-power-point tracking has been employed, so that manufacturer's data for the nominal power output of a module at its maximum power point may be assumed under standard conditions. A thermal model then estimates the effect of ambient temperature and heat generation within the PV module.

The power supplied by the PV system can be calculated as a function of the solar radiation as follows [14]:

$$P_{gen} = P_{N-pv} \frac{G_{T,\beta}}{G_{ref}} \left[1 + k_T \left((T_{amb} + 0.0256G) - T_{ref} \right) \right] \text{ [kW]} \quad (46)$$

where P_{N-pv} is nominal PV output [kWh] with received irradiance G_{ref} at the reference temperature T_{ref} , $G_{T,\beta}$ is the received solar radiation [W/m^2], G_{ref} is 1000 [W/m^2], T_{ref} is 25 °C, $k_T = -3.7 \times 10^{-3}$ [$^{\circ}\text{C}^{-1}$] is the power temperature coefficient and T_{amb} is the ambient

temperature. Inverter inefficiency degrades the achievable PV output and is incorporated in the software model.

5.2 Wind model

The power output of a wind turbine can be approximated by the following formula:

$$P_{gen} = \begin{cases} 0 & v < v_{cutin}, v > v_{cutout} \\ v^3 \left(\frac{Pr}{v_r^3 - v_{cutin}^3} \right) - Pr \left(\frac{v_{cutin}^3}{v_r^3 - v_{cutin}^3} \right) & v_{cutin} \leq v < v_{rated} \\ Pr & v_{rated} \leq v \leq v_{cutout} \end{cases} \quad (47)$$

where Pr is the rated power [kW], v is the wind speed (ms^{-1}) in the current time step, v_{cutout} , v_{rated} , v_{cutin} represent cut-in wind speed, nominal wind speed for rated power and cut-out wind speed (ms^{-1}) respectively. Wind speed data are required as input to the generator model. Since the wind speed varies with height, the measured wind speed at the anemometer must be converted to the desired hub height according to [15].

$$\frac{v_2}{v_1} = \left(\frac{h_2}{h_1} \right)^\alpha \quad (48)$$

where v_2 is the speed at the hub height h_2 , v_1 is the speed at the reference height h_1 and α known as the friction coefficient or Hellman coefficient and depends on the location, terrain on the ground and stability of the air [16].

5.3 Battery mathematical model

Low-level battery models may be based on chemical or electrical analogues and charge accumulation and/or empirical models. Defining a general model which covers all categories simultaneously is quite complex, hence most battery modelling focus on specific characteristics only.

The energy capacity [Wh] of a battery is defined by the energy that a fully charged battery can deliver under specified conditions. Depth of Discharge (DOD) is the ampere hours removed from a fully charged battery and is defined as the percentage ratio of the battery rated capacity to the applicable discharge rate [A]. The battery capacity of the renewable energy system can be initially estimated using the load demand and the required days of autonomy using the following equation [17]:

$$CB = \frac{E_L AD}{V_B DOD_{\max} T_{cf} \eta_{inv} \eta_b} [Ah] \quad (49)$$

where E_L is the load, AD is autonomy days (typically 2–3 days), V_B is the operating voltage of the battery [V], $DOD_{\max}$ is the max depth of discharge (typically 80%), T_{cf} is the temperature correction factor, η_{inv} and η_b are the inverter (typically 95%) and battery (typically 85%) efficiency [11, 18].

State of Charge (SOC) can be defined as the ratio of available capacity to the rated capacity in Ampere-hours [Ahr] and can be estimated using the following equation:

$$SOC = \frac{B_{AC}}{B_{RC}} [Ah] \quad (50)$$

where B_{AC} is the available capacity of the battery [Ah] and B_{RC} is the rated capacity of the battery [Ah].

In a hybrid renewable energy system, the mode of operation of the battery whether it is discharging or charging depends on the available renewable energy in the system and the load. In order to avoid gassing and over-charging the battery is bound by maximum and minimum state of charge constraints. The charging of a battery at any instant $t + \Delta t$ can be estimated with the following equation [19]:

$$SOC(t) = SOC(t-1)(1-\sigma) + \frac{P_{ch}}{P_{bat}} \eta_{ch} [\%] \quad (51)$$

where σ is an hourly self-discharge rate, P_{ch} is the required power to charge or discharge, P_{bat} is the available battery power, η_{ch} is the coulomb efficiency of the battery, $SOC(t-1)$ is the previous state of charge and $SOC(t)$ is the current state of charge.

Another battery model for state of charge can be expressed as an equivalent circuit where the internal voltage is represented by a voltage source and an internal resistance [13]. The charging or discharging current depends on the system's voltage levels. If the applied voltage is greater than the battery's voltage, the current will flow in the battery as a charging current [11]. Meanwhile, if the applied voltage is less than the battery's voltage battery, the current will flow out from the battery as a discharging current.

5.4 Generator model

Generators are not renewable energy options due to their high operating emissions but can provide a steady source of power when renewables are not available and the energy storage is depleted. In principle the environmental cost over lifetime of a small diesel generator could potentially be lower than oversizing the renewable component. The hourly fuel consumption of the diesel generator is considered in the renewable energy system and can be expressed as follows [19]:

$$q(t) = aP_{gen}(t) + bP_r \text{ [l/hr]} \quad (52)$$

where $q(t)$ is fuel consumption [L/h], P_g is generated power [kWh], P_r is rated power [kWh], a and b are constant coefficients of the fuel consumption curve [l/kW] and is approximated to 0.246 and 0.08415 respectively [19].

5.5 Fuel cell model

A fuel cell is an electrochemical energy conversion device, which converts chemical energy of fuel directly into electricity. There are several different types of fuel cells depending on their electrolyte such as Proton Exchange Membrane (PEM) fuel cell, Alkaline fuel cell, Molten Carbonate fuel cell and Solid Oxide fuel cell of which the PEM fuel cell is showing promise due to its low operation and quick start up. Fuel cell modelling can be classified into three categories, analytical, semi-empirical and mechanistic. Analytical methods arrive at V-I density relationships through simple assumptions and neglect water transport processes in the cell. Semi-empirical modelling combine theoretically derived differential and algebraic equations and it is seen that most fuel cells are one dimensional semi empirical models. Mechanistic models are based on electrochemical, thermodynamic and fluid dynamic equations and require details such as transfer coefficients, humidity levels, membrane, electrode and active catalyst layer thicknesses.

The hydrogen consumption of the fuel cell is modelled as dependent on the output power and can be expressed with the following function [11]:

$$fc_{H_2} = \alpha_{fc} fc_{pnom} + \beta_{fc} fc_p \text{ [kg/hr]} \quad (53)$$

where fc_{H_2} is the hydrogen consumption [kg/hr], fc_p is the fuel cell output power [kW], fc_{pnom} is the nominal fuel cell output power [kW], α_{fc} and β_{fc} are the coefficients of the electrical consumption curve [kg/kWh]. In the presented optimisation model $\alpha_{fc} = 0.004$ kg/kWh and $\beta_{fc} = 0.05$ kg/kWh [11].

5.6 Electrolyser model

The hydrogen needed for power generation in a PEM fuel cell is extracted from water in an electrolyser via electrolysis. In the process of electrolysis, the water molecules are

decomposed into its constituent elements, water and oxygen. An electrolyser is hence a series of cells each containing a positive and negative electrode immersed in electrically conductive water where hydrogen and oxygen gases are produced at the cathode and anode respectively. The rate of hydrogen generation depends on the current density.

The electrolyser electrical consumption can be modelled as a function of nominal hydrogen mass flow [11]

$$p_{ele} = \alpha_{ele} Q_{n-H_2} + \beta_{ele} Q_{H_2} \text{ [kW]} \quad (54)$$

where p_{ele} is electrolyser electrical consumption [kW], α_{ele} , β_{ele} are the coefficients of the electrical consumption curve [kW/kg/hr], Q_{n-H_2} is the nominal hydrogen mass flow [kg/hr] and Q_{H_2} is the actual hydrogen mass flow [kg/hr].

The availability of hydrogen in a hybrid energy system can be expressed as follows:

$$SOC_{ele} = \int (p_{ele} \eta_{ele}) dt - \int \frac{p_{fc}}{\eta_{fc}} [kW] \quad (55)$$

where p_{ele} [kW] is the power available to run the electrolyser and is the remaining power after the load has been satisfied ($p_{ele} = p_{ren} - E_L$), p_{fc} [kW] is the power generated by the fuel cell stack, η_{ele} [%] and η_{fc} [%] is the efficiency of the electrolyser and fuel cell respectively.

5.7 Hydrogen storage model

One of the most crucial factors in simulation of hydrogen storage in HRES models is to calculate its available hydrogen tank level at any point in time. The expression used to calculate the current hydrogen level, implements a typical hourly flow balance between the input and the hydrogen output flow in the tank. The hydrogen level of the H_2 tank H_2 level at

time step t depends on the previous hydrogen level at time step $t-1$ and can be calculated as follows:

$$H_2 \text{ level}(t) = H_2 \text{ level}(t-1) + Q_{H_2}(t) - \frac{fc_{H_2}}{\eta_{H_2 \text{ tank}}} [\text{kg}] \quad (56)$$

where $H_2 \text{ level} [\text{kg}]$ is the hydrogen level of the hydrogen tank, $Q_{H_2} [\text{kg/hr}]$ is the mass flow of hydrogen from the electrolyser, $fc_{H_2} [\text{kg/hr}]$ represents the fuel cell hydrogen consumption and $\eta_{H_2 \text{ tank}} [\%]$ is the efficiency of the hydrogen storage tank and is set to 5% [11].

6 Case studies

6.1 Case study 4

Case Study 4 is based on set out cases by Sharafi and Elmeikkawy [5] and Dufo-López and Bernal-Agustín [8]. Sharafi and Elmeikkawy set out different tests using various *LPSP* and CO2 emission constraints (Table 2 in [5]) where Case Study 4 emulates SC Case 3 [5] and BD Case 3 [8] ($LPSP = 1.8\%$, $\varepsilon_{gen} = 1778 \text{ kg/yr}$). These constraints originate from system outputs found by Dufo-López and Bernal-Agustín [8].

The test cases are summarised in Table 2.

Table 2: Test cases benchmarked and analysed

Case Study	Reference	PV(kW)	Wind (kW)	Diesel generator (kW)	Fuel cell (kW)	Battery (kWh)	Electrolyser (kW)	H2-tank (kg)
4	Sharafi and Elmeikkawy [5] Dufo-López and Bernal-Agustín [8] SE Case 3	8	6.5	3	0.11	88.7	1.1	4.2
4	Sharafi and Elmeikkawy [5] Dufo-López and Bernal-Agustín [8] DB Case 3	8	6.5	3	3	88.7	4	10

Sharafi and Elmeikkawy plotted average monthly wind speeds during one year from Zaragoza in Spain, latitude 41.6488° N , 0.8891° W , Time Zone: - GMT+2 and plotted a daily

load profile for each month in kWh. These daily load profiles and average wind speeds were used algorithmically to simulate a year of data in order to carry out the optimisation modelling (Figure 3, Figure 4, Figure 5). The annual load, PV and wind generation were emulated according to annual figures given by Dufo-López and Bernal-Agustín [8].

Figure 3: Building data showing annual (1st January 2016 to 31st December 2016) and daily load data respectively.

Figure 4: Weather and building data showing annual (1st January 2016 to 31st December 2016) solar, temperature, wind and load data respectively.

Figure 5: Typical winter (27th July 2016) and summer (27th January 2016) daily weather data showing

A case study was set up based on an energy system with PV, wind, battery bank, generator, fuel cell, electrolyser and hydrogen tank (Figure 6) by Sharafi and Elmekawy [5] using a 100% economic weighting with the generated solar, wind data and load and a

technical ($LPSP = 1.8\%$ maximum) constraint and environmental constraint ($\varepsilon_{gen} = 1778$
kg/year maximum) according to SE Case 3 and BD Case 3 [5, 8] in Table 2.

The load is supplied by solar/wind-generated electricity when available. Surplus energy is used to charge the battery. If the battery has been charged to its maximum SOC, any surplus energy is fed to the electrolyser to generate hydrogen for storage in the hydrogen tank. When there is a deficiency in the solar/wind resource, the battery will supply the deficit until it has reached its minimum SOC. If the battery cannot satisfy the full residual load, then the fuel cell will satisfy the remainder provided there is enough hydrogen in the hydrogen tank to do so. If the fuel cell cannot satisfy the needed portion of load then the generator will try to fulfil the remainder of the load demand. Once the load has been satisfied by the diesel generator, any surplus energy will be used to charge the battery bank as this will ensure that maximum generated energy is utilised in the stand alone system leading to minimum excess energy.

Figure 6: Block diagram for case study 4

Component specifications and costings used in the optimisation originate from the project costs in [5, 8] where initial cost and capital costs are extrapolated from graphs in [5] and have been summarised in Table 3. Assessment period is 25 years, discount rate is set to 8% and real interest rate is set to 13% [5]. Typical system losses [20] of 11.42% are applied with an actual PV inverter efficiency of 97% for the roof inverters. The electrolyser capacity is set to 10% implying that hydrogen will be generated once 10% of the full electrolyser electrical consumption is available. This figure was based on a discussion with a manufacturer of PEM electrolysers.

Table 3: Component costings for Case study 4

Device component	Device characteristics	Cost (€) Based on extrapolation from economic graphs in [5]
PV	Maximum power: 255W/panel Efficiency: 12% Poly crystalline solar cells PV panel area: 1.046 m×1.588 m System losses: 7% Temperature reference: 25 C Life time: 24 years [5]	Initial cost: €5852/kW [Euro] [5] OM: €29.6/kW/year [Euro] [5] Replacement cost: 100%
Battery	Efficiency: 95% Battery discharge efficiency: 100% Battery charge efficiency: 90% Depth of discharge: 70% Battery inverter efficiency: 85% SOC max: 100% SOC min: 30% Life time: 5 years [5]	Initial cost: €1795/kWh [Euro] [5] OM: €308/kWh/year [Euro] [5] Replacement cost: 100%
PEM electrolyser	Electrolyser efficiency: 95% Electrical consumption Alpha: 20 kWh/kg Electrical consumption Beta: 40 kWh/kg Life time: 10 years [5]	Initial cost: €7226/kW [Euro] [5] OM: €39.7/kW/year [Euro] [5] Replacement cost: 100%
Metal hydride storage tank	Hydrogen tank efficiency: 95% H ₂ max: 100% of H ₂ capacity H ₂ min: 5% of H ₂ capacity Life time: 10 years [5]	Initial cost: €5852/kW [Euro] [5] OM: €0.10/kW/year [Euro] [5] Replacement cost: 100%
PEM fuel cell	Efficiency: 50% Max efficiency: 50% LHV: 33.3 kWh/kg HHV: 39.39 kWh/kg Life time: 15000 hours [5]	Initial cost: €1000/kg [Euro] [5] OM: €50/kg/year [Euro] [5] Replacement cost: 100%

The authors reported trials of two methods for optimising the system. The first method SE Case 3, that of Sharafi and Elmeikkawy, yielded a configuration with a PV size of 8.0 kW, 6.5 kW wind, 3.0 kW diesel generator, 0.1 kW fuel cell, 88.7 kWh battery capacity, 1.1 kW electrolyser and 4.2 kg H₂ storage. The second method DB Case 3, that of Dufo-López and Bernal-Agustín [8], yielded a configuration with a PV size of 8.0 kW, 6.5 kW wind, 3.0 kW diesel generator, 3.0 kW fuel cell, 88.7 kWh battery capacity, 4.0 kW electrolyser and 10.0 kg H₂.

6.1.1 Results and Discussion

It should be noted that the optimisation was over economic cost minimisation, subject to upper limits on the LPSP and operating emissions. As the objectives in question had not been given by Dufo-López and Bernal-Agustín, $LPSP$ and ε_{gen} had to be calculated for the Sharafi and Elmeikkawy and Dufo-López and Bernal-Agustín methods in order to be benchmarked against the PSO algorithm. Running the obtained optimum device sizes found by Sharafi and Elmeikkawy method for SE Case 3 [5] (8.0 kW PV, 6.5 kW wind, 3 kW diesel, 0.11 kW fuel cell, 88.7 kWh battery, 1.1 kW electrolyser and 4.2 kg H₂ tank) using the same input data in the proposed optimisation algorithm, found an $LPSP$ value of 0.8 %, an emission limit of 1128 kgCO₂eq and a cost of 118,296 Euro. The Dufo-López and Bernal-Agustín method DB Case 3 (8.0 kW PV, 6.5 kW wind, 3 kW diesel, 3 kW fuel cell, 88.7 kWh battery, 4 kW electrolyser and 10 kg H₂ tank) obtained an $LPSP$ of 0.8 %, a ε_{gen} of 969 kgCO₂eq and a total project cost of 186,728 Euro. The TEL value from the renewable energy component is reasonable (9812 kWh/year) for both systems.

While both methods employed by Sharafi and Elmeikkawy and Dufo-López and Bernal-Agustín lead to configurations that are within the constraints for reliability and emissions, it

is observed that the electrolyser doesn't run at all for the whole duration of the simulation period and hence doesn't fill the hydrogen tank once the hydrogen level is low. As the electrolyser does not have enough surplus energy to operate, the system configuration leads to unutilised components and an unnecessarily complex configuration and high system cost for little return. In SC Case 4 and DB Case 4, the fuel cell is sized too low and will in most cases never satisfy the deficit load without having to run the diesel generator as well. It is concluded that the energy system places much of its supply reliability in the hands of the battery bank (5806 to 5757 hours/year). In order to make it worthwhile to install the hydrogen fuel cell component and utilise it more frequently throughout the year, the system reliance on other storage devices should be reduced. Therefore the generator is proposed to be sized to only handle the minimum load (up to 0.5 kW) and the battery sized to handle max a day's load (37 kWh).

With a hydrogen fuel cell energy system in mind, the PSO configuration boundaries are initialised to a battery max size of 1 day's autonomy (37 kWh), a hydrogen tank equivalent to 4 day's battery capacity (10 kg), the generator max boundary to the minimum load (0.5 kWh), the fuel cell and electrolyser range set to the maximum load (5 kW) and the PV and wind size up to 10 kW. The building load is fairly small (min 0.47 kW, max 4.18 kW, average 1.6 kW) hence it seems unnecessary to oversize the system much more than the set ranges. These ranges ensured a system which wasn't oversized within similar economic frameworks to the benchmark tests whilst ensuring a more efficient operation. The fuel cell never operates at its peak as seen in output graph Figure 9 as the battery is heavily relied upon first before the fuel cell is used. The optimisation model found a system configuration with $LPSP = 1.0 \%$, $\epsilon_{gen} = 59 \text{ kgCO}_2\text{eq}$, both well below the declared constraints, with an optimised cost of 213,200 Euro for the whole system. The system device sizes were 10.0 kW PV, 10 kW wind generator, 0.5 kW diesel generator, 37 kWh battery capacity, 5 kW

electrolyser size capacity, 4.2 kW fuel cell capacity and 11.0 kg H₂ storage. As expected the system life cost is higher for the optimised system compared to Sharafi and Elmekkawy and Dufo-López and Bernal-Agustín methods as the hydrogen fuel cell component is geared to be more utilised with less input from the battery bank and generator. It is observed that the electrolyser generates hydrogen for a fair part of the year and the fuel cell contributes to satisfying the deficit load continuously throughout the year. The operational hours of the generator through out the year are kept at a minimum as well as the battery operational hours. The LPSP with this arrangement is 1.0% and it is seen that deficit energy occurs towards the end of the year in Figure 7 and Figure 8.

The results are summarised in Table 4.

Figure 7: Test Case 4 Annual (1st January 2016 to 31st December 2016) system analysis

A typical summer (31st January) and winter (31st July) day for daily load, surplus energy and deficit energy is shown in Figure 8 for the proposed system. On these particular days there is no shown deficit but surplus energy appears during the day between 9 am and 6 pm on both typical winter and summer days.

Figure 8: Test Case 4 Typical summer (31st January 2016) and winter (31st July 2016) load, deficit and surplus analysis.

757 **Table 4: Optimisation output for Case Study 4**

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<p>System configuration – PV+wind+battery+electrolyser+hydrogen tank + fuel cell</p> <p>Weighting:</p> <p>Technical weighting : 0 % Economic weighting : 100 % Environmental weighting : 0 % Socio-political : 0 %</p> <p>User Constraint Optimisation:</p> <p>User tech constraint : 1.8 [%] User economic constraint : Inf [1000 Euro] User environmental constraint : 1778.0 [kgCO₂eq] User socio-political constraint : Inf</p>		
<p>Optimisation by Sharafi and Elmekkawy [5] Reference case SE Case 3</p>	<p>Optimisation by Dufo-López and Bernal-Agustín [8] Reference case DB Case 3</p>	<p>Proposed optimisation Figure 7, Figure 8, Figure 9, Figure 10, Figure 11, Figure 12 Figure 13, Figure 14, Figure 15, Figure 16, Figure 17</p>
<p>Best Constraint Optimisation:</p> <p><i>LPSP</i> : 0.8 [%] <i>NPV</i>: 118. 4[1000 Euro] $\mathcal{E}_{gen}$: 1128 [kgCO₂eq] <i>Socio</i> : 0</p> <p><i>TEL</i> : 9812 [kWh]</p> <p>Building load: 1.4×10^4 [kWh/yr] Maximum load: 4.2 kWh Minimum load: 0.5 kWh Average load: 1.6 kWh</p> <p>PV generation: 8369.9 [kWh/yr] Wind generation: 8642.0 [kWh/yr] Battery energy generation: 5805.9 [kWh] Battery discharge hours: 3910.0 [hrs/yr] Generator operation: 479.1 [hrs/yr] Electrolyser operation: 0.0 [hrs/yr] Fuel cell generation: 64.7 [kWh/yr] Fuel cell operating hours: 606 [hrs/yr]</p> <p>Unmet load: 110.1 [kWh/yr] Excess load: 3624 [kWh/yr]</p> <p>Best Constraint System:</p> <p>pv size: 8.0 [kW] wind size : 6.5 [kW] gen size : 3.0 [kW] bat size : 88.7 [kWh] elec size : 1.1 [kW] fc size : 0.1 [kW] H₂ size : 4.2 [kg]</p>	<p>Best Constraint Optimisation:</p> <p><i>LPSP</i> : 0.8 [%] <i>NPV</i>: 186.7 [1000 Euro] $\mathcal{E}_{gen}$: 969 [kgCO₂eq] <i>Socio</i> : 0</p> <p><i>TEL</i> : 9812 [kWh]</p> <p>Building load: 1.4×10^4 [kWh/yr] Maximum load: 4.2 kWh Minimum load: 0.5 kWh Average load: 1.6 kWh</p> <p>PV generation:8369.9 [kWh/yr] Wind generation: 8642.0 [kWh/yr] Battery energy generation: 5759.6 [kWh] Battery discharge hours: 3910.0 [hrs/yr] Generator operation: 403.7 [hrs/yr] Electrolyser operation: 0.0 [hrs/yr] Fuel cell generation: 158.5 [kWh/yr] Fuel cell operating hours: 200.0 [hrs/yr]</p> <p>Unmet load: 113.9 [kWh/yr] Excess load: 3624.5 [kWh/yr]</p> <p>Best Constraint System:</p> <p>pv size: 8.0 [kW] wind size : 6.5 [kW] gen size : 3.0 [kW] bat size : 88.7 [kWh] elec size : 4.0 [kW] fc size : 3.0 [kW] H₂ size : 10.0 [kg]</p>	<p>Best Constraint Optimisation:</p> <p><i>LPSP</i> : 1.0 [%] <i>NPV</i> : 213.2 [1000 Euro] $\mathcal{E}_{gen}$: 59 [kgCO₂eq] <i>Socio</i> : 0</p> <p><i>TEL</i> : 2.4×10^4 [kWh]</p> <p>Building load: 1.4×10^4 [kWh/yr] Maximum load: 4.2 kWh Minimum load: 0.5 kWh Average load: 1.6 kWh</p> <p>PV generation:1.0×10^4 [kWh/yr] Wind generation:2.1×10^4 [kWh/yr] Battery energy generation: 5614.5 [kWh] Battery discharge hours: 3081.0 [hrs/yr] Generator operation: 24.6 [hrs/yr] Electrolyser operation: 72.0 [hrs/yr] Fuel cell generation: 208.7 [kWh/yr] Fuel cell operating hours: 169.0 [hrs/yr]</p> <p>Unmet load: 138.7 [kWh/yr] Excess load: 1.7×10^4 [kWh/yr]</p> <p>Best Constraint System:</p> <p>pv size : 10.0 [kW] wind size : 10.0 [kW] gen size : 0.5 [kW] bat size : 37.0 [kWh] elec size : 5 [kW] fc size : 4.2 [kW] H₂ size : 11.0 [kg]</p>

When analysing the proposed system, it is seen from analysis of the energy generation streams (renewable, battery and fuel cells) that the battery is utilised fairly consistently throughout the year but with overall less annual discharge hours (3081 hrs/yr) compared to [8] (3910 hrs/yr) with use of the fuel cell towards the end of the year (Figure 9). The fuel cell annual kWh generation (208.7 kWh) is more than in [8] (54.7 to 158.5 kWh). The generator annual operational hours have decreased drastically from 479.1 and 403.7 hrs/yr to 24.6 hrs/yr.

Figure 9: Test Case 4 Annual (1st August 2016 to 1st August 2017) renewable output analysis

The battery is seen to discharge and charge consistently throughout the year. Figure 10 shows annual battery kWh discharge, charge and SOC throughout the simulation and optimisation period.

Figure 10: Test Case 4 Annual (1st August 2016 to 1st August 2017) battery analysis

A typical summer (31st January) and winter (31st July) day for battery charging, discharging and SOC is shown in Figure 11 for the proposed system. For the typical days, the battery appears to mainly be discharging after 7 pm on both typical winter and summer days and be charging in a similar pattern on both days between 2 am and 9 am.

Figure 11: Test Case 4 Typical summer (31st July 2016) and winter (31st January 2017) battery analysis

The system's hydrogen generation and hydrogen consumption in the energy system during the simulation and optimisation period is demonstrated next. Figure 12 shows annual hydrogen flow from the hydrogen storage tank, fuel cell hydrogen consumption and

equivalent fuel cell electrical output throughout the simulation and optimisation period for the proposed system and indicates that there is activity from the fuel cell only towards the end of the year.

Figure 12: Test Case 4 Annual (1st January 2016 to 31st December 2016) hydrogen storage discharge hydrogen flow analysis

As expected the only time when there is fuel cell electricity generation is when the fuel cell hydrogen intake occurs, which coincides with the outflow of hydrogen from the hydrogen tank. For these typical days the fuel cell is not running. As estimated the only time the electrolyser consumes electricity is when it generates hydrogen for storage in the hydrogen tank and a linear correlation is observed between the level of hydrogen generated by the electrolyser and its electrical consumption (Figure 13). The hydrogen tank is only discharged towards the end of the year. Once the hydrogen tank reaches a certain level, the electrolyser generates hydrogen.

Figure 13: Test Case 4 Annual (1st August 2016 to 1st August 2017) hydrogen storage charge hydrogen flow analysis

A typical summer (31st July) and winter (31st January) day for electrolyser hydrogen production, hydrogen storage level and electrolyser consumption is shown in Figure 14 for the proposed system. It appears from these typical winter and summer days that hydrogen remains the same in the hydrogen tank with no generation from the electrolyser.

Figure 14: Test Case 4 Typical summer (31st July 2016) and winter (31st January 2017) hydrogen storage charge analysis

It is seen from Figure 15 that the objectives converge as the PSO search function searches through the search space for an optimised system with the set out economic

weighting and technical and environmental constraint. The Figure 16 Ec vs Env and Tech vs Ec respectively for an economic weighting is of particular interest as it shows the interaction between the emission and NPV and LPSP and NPV respectively. As expected the higher the NPV cost, the lower the LPSP value and the higher the NPV value the higher emission cost. The bottom right figure Tech vs Ec vs Env in Figure 17 incorporates the environmental objective as a 3D view to show the interaction between the technical, economic and environmental objective in its entirety.

Figure 15: Test 4A - Individual objectives for case study 4 for 100% economic NWCMO with user constraints

Figure 16: Test 4A - 2D multi objectives for case study 4 for 100% economic NWCMO with user constraints

Figure 17: Test 4A - 3D multi objectives for case study 4 for 100% economic NWCMO with user constraints

To demonstrate optimisation of a system with four objectives simultaneously and to show the significance of the socio-political objective, suppose a local negative perception exists towards diesel generators due to emissions, capital outlay and maintenance concerns. The project should instead demonstrate a clear reliance on electrolyzers, fuel cells and hydrogen tanks whilst being backed up by batteries for three days autonomy to be perceived as more sustainable locally. Consequently the categories Aesthetics, Hazard, Local environmental impact and Renewable Factor lead to an unacceptable public and political acceptance whenever a system shows a high reliance on diesel generators. The LPSP and emission constraints still remain at the set out boundaries. The model was configured using the socio-political index to eliminate generators and increase the hydrogen component whilst adjusting remaining device size ranges to maintain the emission limits with little emphasis on supply reliability. An optimisation test was carried out to maintain the *LPSP* and emission limit, whilst eliminating the diesel generator, introduce a 3 day battery backup and lean more on the hydrogen fuel cell component. A balance had to be struck between the sizes of the renewables versus hydrogen storage to ensure that the fuel cell and electrolyser operated

enough hours throughout the year to demonstrate the hydrogen fuel cell component. The result was an *LPSP* of 1.0%, 0 kgCO₂eq, a system cost of 234,148 Euro, equivalent to 10.0 kW PV, 10.0 kW wind, 111 kWh battery, 4.2 kW fuel cell, 5.0 kW electrolyser and 11.0 kg H₂. As expected, a higher input of hydrogen and its constituent components, plus a 3 day battery backup eliminates the need for a diesel generator. The emissions are 0 kgCO₂eq as only diesel generator emissions are considered in Case Study 4 to emulate SE Case Study 3 and DB Case Study 3. A more appropriate way of analysing an energy system's footprint is to analyse the total system emissions. Despite the high system cost, the system would serve as a good pilot study for the integration of hydrogen storage in renewable energy systems.

The results are summarised in Table 5.

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857 **Table 5: WNCMO minimisation for case study 4**

System configuration – PV+wind+battery +electrolyser+hydrogen tank + fuel cell
Weighting: Technical weighting : 0 % Economic weighting : 100 % Environmental weighting : 0 % Socio-political : 0 % User Constraint Optimisation: User tech constraint : 1.8 [%] User economic constraint : Inf [1000 Euro] User environmental constraint : 1778.000 [kgCO ₂ eq] User socio-political constraint : 10 [kWh]
Proposed optimisation
Best Optimisation: <i>LPSP</i> : 1.0 [%] <i>NPV</i> : 234.1 [1000 Euro] <i>E_{gen}</i> : 0 [kgCO ₂ eq] <i>Socio</i> : 6.9 <i>TEL</i> : 1.9×10 ⁴ [kWh] Building load: 1.4×10 ⁴ [kWh/yr] Maximum load: 4.2 kWh Minimum load: 0.5 kWh Average load: 1.6 kWh PV generation:1.0×10 ⁴ [kWh/yr] Wind generation: 2.1×10 ⁴ .0 [kWh/yr] Battery energy generation: 5694.6 [kWh] Battery discharge hours: 3081.0 [hrs/yr] Generator operation: 0.0 [hrs/yr] Electrolyser operation: 33.0 [hrs/yr] Fuel cell generation: 191.4 [kWh/yr] Fuel cell operating hours: 164.0 [hrs/yr] Unmet load: 140.0 [kWh/yr] Excess load: 1.7×10 ⁴ [kWh/yr] Best Constraint System: pv size : 10.0 [kW] wind size : 10.0 [kW] gen size : 0 [kW] bat size : 111 [kWh] elec size : 5.0 [kW] fc size : 4.2 [kW] H ₂ size : 11.0 [kg]

6.2 Case study Cold Stream

This section outlines a case study where the proposed search model has been applied for a techno-economic optimisation study to analyse and optimise a solar and wind farm in South Australia to increase supply reliability whilst minimising cost by incorporating battery capacity, fuel cell, electrolyser and hydrogen storage. The socio political objective is explored to rectify the system's supply reliability with a hydrogen fuel cell component focus.

A techno-economic-socio-political study using the developed optimisation model by Eriksson and Gray has been undertaken of a proposed large 250 kWp solar and 95 kWp wind generation plant near ColdStream in south Australia at a longitude of 45.4°, a latitude of 37.3° and a time difference of +11 GMT. The tilt angle of the PV panels are assumed to be the same as the latitude angle. The weather data is shown in Figure 18 and Figure 19 and has been simulated based on available BOM data from the region.

The system has been analysed from a distributed network point of view off grid to determine optimum storage to achieve a certain reliability of supply whilst minimising the cost function. The supply reliability is calculated as Loss of Power Supply Probability (*LPSP*) and the cost as Net Present Value (*NPV*) outlined in paper by Eriksson and Gray. In addition to an economic and technical objective, an environmental objective as the total emissions of the system ϵ_{sys} is calculated. The socio political objective is explored to rectify the system's supply reliability with a hydrogen fuel cell component focus. Economic parameters for the *NPV* function are a discount rate of 8%, a real interest rate of 13%, a fuel inflation rate of 5% and a project life time of 24 years.

The load pattern is actual metered data in 2016 from a conference centre in the Coldstream area provided by stakeholders of the premises. The annual load is 56,033 kWh with a min, max and average hourly load of 0, 37.9 and 6.4 kWh respectively.

Figure 18: Annual (1st January 2016 to 31st December 2016) weather data in Coldstream, south Australia

Figure 19: Typical summer (31st January 2016) and winter (31st July 2016) solar radiation, temperature and wind speeds in Coldstream, south Australia

The energy system in Coldstream was simulated firstly in its current proposed configuration (250 kWp PV system and a 95 kWp wind system) using the generated solar radiation, wind data, ambient temperature and actual load to analyse its current supply reliability.

To ensure better reliability, it is proposed to integrate storage devices such as a battery bank in conjunction with electrolyser, hydrogen tanks and fuel cells into the energy system whilst reducing the renewable generation plant size. A techno-economic optimisation is hence carried out to maintain the LPSP at between 0.5% and 3% whilst minimising the NPV. For demonstration purposes of hydrogen capability, the devices are constrained for a system with a high reliance on a hydrogen fuel cell component in conjunction with weightings applied in the socio-political objective. The optimisation ranges are set to a PV range between 40 kW – 100 kW, wind range to 30 – 80 kW, fuel cell size between 80 and 100 kW, electrolyser between 5 and 45 kW, battery backup of between 2 and 38 kWh (up to 25% of a day's autonomy) and hydrogen storage between 4.6 and 46 kg equivalent to a range between 1 and 10 times the battery capacity.

The optimised PV inverter output generation for the whole simulation period is shown in Figure 20.

Figure 20: Test Case 31 Annual (1st January 2016 to 31st December 2016) PV, wind and renewable power output

A typical summer (31st January) and winter (31st July) day for PV, wind and total renewable power output is shown in Figure 21. The daily summer and winter typical PV inverter output displays generation in particular early in the morning until 3 pm.

Figure 21: Test Case 31 Typical summer (31st January 2016) and winter (31st July 2016) system renewable power analysis

The optimisation achieves an LPSP of 1.3% (Figure 22) with a 51.2 kWp PV system, 46.9 kWp wind, a battery size of 38 kWh (38% of a day's load requirement of 98 kWh), an electrolyser and a fuel cell size of 45.0 kW and 44.0 kW respectively (based on surveyed surplus load and max building load) and a hydrogen storage tank of 46.0 kg (hydrogen electrical equivalent storage capacity is 10 times a day's usable battery capacity of 153 kWh). The NPV and emissions are \$7,067,588 USD and 229.4 TCO₂eq respectively.

Figure 22: Test Case 31 Annual (1st January 2016 to 31st December 2016) system analysis showing system load, energy surplus and energy deficit

A typical summer (31st January) and winter (31st July) day for building load, deficit and surplus load is shown in Figure 23. A typical summer day shows no deficit whilst a winter day shows deficit for an hour around midnight. Surplus for a typical summer day occurs up to around 3 pm whilst in winter surplus only occurs for two hours from 5 am.

Figure 23: Test Case 31 Typical summer (31st January 2016) and winter (31st July 2016) system analysis showing system load, energy surplus and energy deficit

Results are summarised in Table 6.

It is seen from analysis of the energy generation streams (renewable, battery and fuel cells) that the battery and fuel cell are utilised fairly consistently throughout the year (Figure 24).

Figure 24: Test Case 31 Annual (1st January 2016 to 31st December 2016) renewable output analysis

Figure 25 shows the convergence of all system input devices as they travel through the PSO search space using the configured PSO algorithm parameters.

Figure 25: Test Case 31 System input device capacity PSO convergence

Figure 26 shows annual battery kWh discharge, charge and charge and State of Charge (SOC) throughout the simulation and optimisation period and indicate the battery is consistently deployed throughout the year.

Figure 26: Test Case 31 Annual (1st January 2016 to 31st December 2016) battery analysis

A typical summer (31st January) and winter (31st July) day for battery charging, discharging and SOC is shown in Figure 27. Discharging occurs after 3 pm in summer for about 8 hours and on a typical winter day for three hours before 10 am. The battery charges briefly for an hour around 1 am in summer and for around four hours before 5 am on a typical winter day.

Figure 27: Test Case 31 Typical summer (31st January 2016) and winter (31st July 2016) battery analysis

Figure 28 shows annual hydrogen flow from the hydrogen storage tank, fuel cell hydrogen consumption and equivalent fuel cell electrical output throughout the simulation and optimisation period.

**Figure 28: Test Case 31 Annual (1st January 2016 to 31st December 2016) hydrogen storage discharge
hydrogen flow analysis**

A typical summer (31st January) and winter (31st July) day for hydrogen outflow from the hydrogen storage tank, the intake of hydrogen flow into the fuel cell and electrical output from the fuel cell is shown in Figure 29. As expected the only time when there is fuel cell

971 electricity generation is when the fuel cell hydrogen intake occurs, which coincides with the
 972 outflow of hydrogen from the hydrogen tank. For a typical winter day the fuel cell generates
 973 electricity after 3 pm onwards with a concurrent discharge of hydrogen from the hydrogen
 974 tank in this period.

975
 976 **Figure 29: Test Case 31 Typical summer (31st January 2016) and winter (31st July 2016) hydrogen**
 977 **storage discharge analysis**

978
 979 The electrolyser consumes electricity in a linear fashion in line with hydrogen
 980 generated for storage (Figure 30). It is observed that the hydrogen tank level is low between
 981 around mid June and beginning of September.

Figure 30: Test Case 31 Annual (1st January 2016 to 31st December 2016) and daily (27th July 2016) hydrogen storage charge hydrogen flow analysis

A typical summer (31st January) and winter (31st July) day for electrolyser hydrogen production, hydrogen storage level and electrolyser consumption is shown in Figure 31. The electrolyser only appears to be generating hydrogen for an hour on a typical summer day at 2 am and in winter around 6 am.

Figure 31: Test Case 31 Typical summer (31st January 2016) and winter (31st July 2016) hydrogen storage charge analysis

It is seen from Figure 32 that the objectives converge as the PSO search function searches through the search space for an optimised system with the set out economic weighting and technical constraint.

Figure 32: Test Case 31 single objectives normalised output in PSO search algorithm

The Ec vs Env and Tech vs Ec respectively in Figure 33 for an economic weighting is of particular interest as it shows the interaction between the emission and *NPV* and *LPSP* and *NPV* respectively. As expected the higher the *NPV* cost, the lower the *LPSP* value and the higher the *NPV* value the higher emission cost.

Figure 33: Test Case 31 2D objectives normalised output in PSO search algorithm

The bottom right figure Tech vs Ec vs Env in Figure 34 incorporates the environmental objective as a 3D view to show the interaction between the technical, economic and environmental objective in its entirety.

Figure 34: Test Case 31 3D objectives normalised output in PSO search algorithm

Results are summarised in Table 6.

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Table 6: Test Case 31 energy system analysis

System configuration – PV+wind	1016
Weighting:	1017
Technical weighting : 0 %	1018
Economic weighting : 100 %	
Environmental weighting : 0 %	1019
Socio-political : 0 %	
User Constraint Optimisation:	1020
User tech constraint : 3 [%]	1021
User economic constraint : Inf [\$ US]	
User environmental constraint : Inf [kgCO ₂ e]	1022
User socio-political constraint : Inf [kWh]	
Simulation with preliminary design	1023
building load and estimated PV inverter output	
Test Case 31	1024
Figure 20, Figure 22, Figure 24, Figure 25,	
Figure 26, Figure 28, Figure 30	1025
Optimisation output:	
LPSP : 1.6 [%]	1026
NPV : 7.1×10 ⁶ [\$ USD]	
$\mathcal{E}_{sys}$: 229.4 [TCO ₂ eq]	1027
Socio : 0.0	1028
TEL : 6.4×10 ⁴ [kWh]	1029
Building load: 5.6x10 ⁴ [kWh/yr]	
Maximum load: 37.9 kWh	1030
Minimum load: 0 kWh	
Average load: 6.4 kWh	1031
PV inverter generation: 8.6×10 ⁴ [kWh/yr]	1032
Wind generation: 1.2×10 ⁴ [kWh/yr]	
Battery energy generation: 1.1×10 ⁴ [kWh]	1033
Battery discharge hours: 3902 [hrs/yr]	
Generator operation: 0 [hrs/yr]	1034
Electrolyser operation: 2251 [hrs/yr]	
Fuel cell generation: 1.1×10 ⁴ [kWh/yr]	1035
Fuel cell operating hours: 1304.0 [hrs/yr]	
Unmet load: 602 [kWh/yr]	1036
Excess load: 2.1×10 ⁴ [kWh/yr]	1037
Best System Configuration:	1038
pv size : 51.2 [kW]	1039
wind size :46.9 [kW]	
gen size : 0.0 [kW]	1040
bat size : 38.0 [kWh]	
elec size : 45.0 [kW]	
fc size : 44.0 [kW]	
H2 size : 46.0 [kg]	

Results and Discussion

Test Case 31 of a proposed solar and wind system with actual metered weather data and building load data, provides an insight into enabling a medium sized commercial premise to generate its own electricity and be off grid with a high supply reliability.

Without storage and using the actual weather data to calculate PV inverter and wind output, it is seen that whilst the renewable energy components are oversized (3.9×10^5 kWh/year) and are larger than the total annual building load (5.6×10^4 kWh), the system does not result in a high supply reliability (33.1%) as energy storage is missing. Facilities used in hospitality would display similar load patterns such as this conference centre where the building load is not necessarily high during the day when solar output is available but also display high usage patterns early in the morning and at night. The early electrical morning and night consumption may occur due to scheduled mechanical services and equipment to run at off peak times to reduce peak loads. It is seen that on a typical summer and winter day the renewable output fails to supply the load after around 3 pm, resulting in the high *LPSP* (33.1%).

The system is analysed and optimised for optimum storage of a larger battery back up and minor hydrogen fuel cell component to obtain an *LPSP* of between 1% and 5%. It is seen that the optimum storage which meets the technical constraints (1.5%) whilst minimises the cost is a reduction in PV and wind size (52.3 kW and 46.9 kW respectively), a battery back up of 38 kWh, 45 kW electrolyser, 44 kW fuel cell and 46 kg hydrogen storage tank (Table 6). The less PV and wind system results in a 478% area reduction ($1,600 \text{ m}^2$ versus 335 m^2) and 50% less footprint (ten 10 kWp wind turbines versus five 10 kWp wind turbines) respectively.

From the output in Table 6 it is seen that the system relies heavily on the battery storage (3902 hours/year) with frequent assistance from the hydrogen component (electrolyser generates hydrogen 2251 hours/year, fuel cell generates 5.6×10^4 kWh and operates 1304 hours/year). The electrolyser control logic which turns on the electrolyser when 10% of the full electrolyser capacity is available allows the fuel cell to contribute to the load fairly consistently throughout the year (Figure 24).

7 Summary and Conclusions

This paper has provided an outline of a new method for simulation and optimisation of hybrid renewable energy systems using a Normalised Weighted Constrained Multi Objective Meta heuristic search technique which takes into account technical, economic, environmental and socio-political objectives concurrently in a weighted fashion with a constraint capability.

Case Study 4 demonstrated several key issues when integrating electrolysers, fuel cells and hydrogen storage tanks in that adequate surplus energy must be available to run the electrolyser, the fuel cell must be adequately sized for the load or the deficit load will rely too much on generators to fill the gap and hydrogen storage tanks must be adequately sized to increase supply reliability. The socio-political objective was introduced to demonstrate a certain social and political stance for a higher reliance on hydrogen fuel cells. As expected the emissions were eliminated as battery backup and hydrogen storage needed to be increased significantly to uphold the supply reliability to the detriment of the project cost.

It should be noted that the environmental objective proposed by Sharafi and Elmekkawy [5] concerned only the diesel emissions from the diesel generator in operation whilst all other device emissions resulting from production and shipment to site were ignored. In the proposed optimisation model, the environmental objective utilises a cradle- to-grave approach which would more realistically look at all components and their emissions during

manufacturing, transportation and deployment. This approach would be the only objective way to look at renewable energy systems as a whole.

By adding energy storage to the current energy system it is seen that the PV and wind system size has been able to be reduced drastically (PV 250 kW to 51.2 kW, wind 95 kW to 46.9 kW) compared to the initial proposed system with just renewable energy whilst reducing the *LPSP* to an acceptable level. This particular study emphasized hydrogen fuel cell technology for demonstration purposes and purposefully steered away from a large battery bank in the PSO optimisation model. This can be achieved by using the socio-political objective to steer the PSO search algorithm in a certain direction. It is found that the test cases in this chapter has emphasized that the configuration can be optimised using the proposed optimisation model by Eriksson and Gray with variable system configuration, boundaries for device ranges, multiple objectives and user constraints.

It is important to consider the full system cost over the life time of the project, rather than just the capital outlay as the life time cost is the true reflection of the cost throughout the project duration. In the current economic climate a system with a hydrogen component with a high system life cost (\$7,067,588 USD) calculated in Test Case 31 would most likely not be installed due to the cost constraints unless the project has been granted government funding. Conventional mature energy storage such as batteries are obviously cheaper than hydrogen fuel cell technology but if long term sustainable storage is sought then hydrogen fuel cell technology is a viable option which can justify the additional capital outlay.

The presented optimisation technique is a versatile tool in that it is able to analyse and optimise any energy system and is able to tailor the result to suit a particular project's emphasis on specific factors or include user constraints which will force the system to be optimised to suit the individual set out constraints.

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Research highlights

- Optimisation search technique which goes beyond the traditional approach of techno and/or economic optimisation of energy systems.
- Optimisation tool to narrow the gap between research and real-world applications.
- More efficient renewable energy system design for technical (reliable), economical (cost efficient), environmental (emission minimisation) and socio-political (acceptability level to the public) optimisation.
- A novel complex multi optimisation approach of renewable energy systems with conventional and/or hydrogen fuel cell storage components for multiple objectives and/or constraints concurrently.

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