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Optimisation and Integration of Hybrid Renewable Energy Storage Systems

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Abstract. This paper discusses renewable energy system concepts and integration techniques, and reviews modelling and optimization techniques for hybrid renewable energy systems for electricity provision. A proposal to use design criteria that are not limited to performance- and cost-related factors is introduced and forms a background to the following discussion. Optimization techniques in relation to constraints, reliability analysis and algorithms are discussed as well as software tools available for modelling/simulation, component sizing and optimization. The focus is on systems incorporating hydrogen, but the ideas presented have general relevance.

1. Introduction

The faster than projected uptake of distributed photovoltaic systems [1] is one example of the ways in which global energy systems are becoming outdated [2] in terms of technological capability. Furthermore, in the new world of the internationally agreed 2 °C climate-change scenario entered in 2016, the approach of designing to meet only goals related to the technology (capacity, availability, reliability) and economics (return on investment, cost to the consumer) must evolve to be able to take into account other goals: environmental goals foremost, especially the sustainability of the entire life cycle of the installation and its constituent materials and waste products, but also those with a social dimension, such as relationship to landscape and noise. Real-world projects are delayed, disrupted or even cancelled owing to non-technical factors. The great majority of optimization studies reviewed address only techno-economic criteria.

Figure 1 illustrates sets of criteria that could be addressed in the optimization of energy systems, with proximity indicating relative weight: technical, based on performance; economic, based on financial factors; environmental, based at minimum on legal requirements for sustainability; and socio-political, addressing public acceptability and facility, for instance. Any of these areas could be emphasized: technical for critical service, environmental for sensitive locations and so on. The virtual exclusion of factors other than technical and economic over many decades, as illustrated in figure 1, has led to the present need for drastic action for more sustainable energy forms. Prioritization of criteria according to the situation and their quantitative inclusion via an algorithm in the optimization methodology can produce well-balanced outcomes.



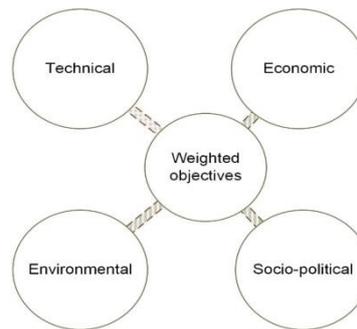


Figure 1. Delineation of criteria for evaluating design outcomes

2. Hybrid energy system integration

Although the load supplied is most likely AC, the generator may be intrinsically AC or DC, and the storage may involve intrinsically AC or DC components. This reality naturally delineates three configurations: DC-coupled, AC-coupled and a hybrid configuration utilizing both DC and AC [3], where “coupled” refers to the electrical bus linking the majority of components. An overarching principle is to minimise the number of energy transformations, since these involve inefficiencies.

In a DC-coupled system the generating components are connected to the bus via DC/DC or AC/DC converters. This configuration can directly feed suitable DC loads, whereas AC loads are fed via a DC/AC converter. Bidirectional converters may be deployed for connected storage components, although batteries may be connected directly to a bus specified for the battery voltage, thus minimising the number of transformations in the energy path. A DC-coupled scheme enables a fairly simple configuration, as synchronization is not required for integration of the various energy sources.

An AC-coupled system integrates generating components such as wind and solar via DC/AC or AC/AC converters. AC loads are fed directly from the bus whereas AC/DC converters feed DC loads. As with the DC-coupled system, a bidirectional inverter may be used for storage systems. Synchronization may be required. In addition, these systems may suffer higher conversion losses, as rectifiers have relatively low efficiency compared to inverters and DC-DC converters [4].

A hybrid DC/AC-coupled configuration has the advantage that it caters for both DC and AC loads, hence eliminating unnecessary energy conversions and increasing the source-to-load efficiency. The downside is that these systems are naturally more complex in terms of control and energy management.

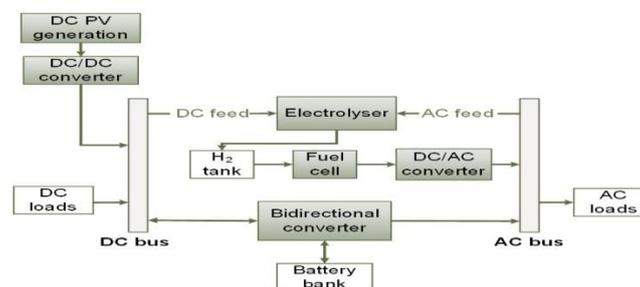


Figure 2. Hybrid bus topology

Individual components may have options for integration, especially electrolysers, which, despite being intrinsically DC, can be purchased as “plug-and-play” AC-powered (fig. 2).

3. Optimisation

Optimization may be seen as getting the best result from the committed resources, including the sources of energy and finance, under constraints derived from the criteria. At the simplest level, the principal output from an optimization process is a specification of the size (energy and/or power capacity) of each component of a system whose configuration was pre-determined. Correct component sizing is the key to achieving a properly functioning system that meets its design goals. At the more sophisticated level, optimization could include an algorithmic approach to settling the system configuration as well, with final parameter values determined by a weighted measure that includes the expanded sets of criteria.

Various configurations of solar/wind hydrogen hybrid energy systems for electricity supply have been studied and reviewed [5], reaching as far back as the 1980's. These energy systems vary in size from 1 kW up to over 600 kW with alkaline and PEM electrolyzers with power capacities between 1 and 320 kW, lead-acid and Li-ion batteries ranging from 42 to 1310 kWh, 30 to 120 bar hydrogen storage and PAFC and PEM fuel cells of capacities from 0.5 to 80 kW. Optimization was generally approached via modelling/simulation based on mathematical models describing the physical (electrical, mechanical, thermal) characteristics of individual components, in other words addressing technological criteria, with cost usually addressed separately.

In purely technical terms, accurate simulation of the performance at system level relies on accurate models of the components. In terms of the reliability of the simulation for a given system in a given location, measured or simulated profiles for the energy input and the load determine whether the simulation is usefully predictive:

4. Evaluation constraints

Constraints on the system design function as boundaries and represent parameters for optimization, and so are the key to finding an optimal solution. Typical constraints applied to designs of renewable energy systems reported in the literature are renewable capacity (e.g. insolation, wind capacity), installation size (e.g. PV area, wind area), physical characteristics (e.g. PV panel tilt angle, wind installation height), battery characteristics (e.g. minimum state of charge, maximum charge/discharge rate, cycle life), environmental restrictions (e.g. pollutant emissions, social acceptability) and various grid integration issues (e.g. power fluctuations of injected power and cost of line extension).

4.1. Implementation

Analysis of the reliability of supply plays a vital role when incorporating renewable energy in energy systems, due to the intermittency of the energy source in most cases. Reliability analysis can be carried out in various ways, the most frequently reported method being loss of power supply probability (LPSP), 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). Other less-often adopted methods to measure reliability of supply include loss of load probability (LOLP), loss of load expected (LOLE), loss of load risk (LOLR), deficiency in power supply probability (DPSP), expected energy not supplied (EENS) and level of autonomy (LOA) [6-8]. These measures are interrelated and are all suitable for an evaluation against technical criteria. Frequently adopted economic criteria are annual system cost (ACS) and levelized cost of energy (LCOE), which are calculated by accounting for all of a system's expected lifetime costs (including construction, financing, fuel, maintenance, taxes, insurance and incentives) and in the case of LCOE then divided by the system's lifetime expected energy output. A frequent environmental criterion is to calculate the generated CO₂ emissions per generating component in the system. A suitable socio-political criterion could be a risk

portfolio evaluation where security of supply is evaluated in line with reliability of renewable and primary energy integration, refer table 1 and table 2. The importance of the latter consideration is illustrated by the severe outage across the Australian state of South Australia in September 2016 [9] when extreme weather disabled a major network at a time when the ~1.5 GW wind power resource was unavailable.

Table 1. Environmental criteria and variables

Environmental criterion	Variables
Emission	Analysis of CO ₂ emissions as units to be minimized.
Fuel consumption	Minimise the total amount of energy consumption taking into account discount factors and cost of imported fuel.
Life cycle	Analysis of Life cycle (cradle-to-grave) emissions generated during the manufacturing, operation and decommissioning of the system.
Waste management	Analysis of the need to dispose of waste during system operation.
Hazard level	Analysis of type of waste and its severity on the environment.

Table 2. Socio-political criteria and variables

Socio-political criterion	Variables
Land acquisition	Visual impact, shadowing, flicker, eco-system disturbance, acoustic noise, electromagnetic interference.
Political acceptance	Analysis of regulations, policies and subsidies released by energy market commissions effecting the energy sector.
Social acceptance	Review of consensus amongst public for energy initiatives and analysis of negative social effects.
Labour	Analysis of employment opportunities in the energy sector.
Social cost of carbon emissions reduction	of Estimation of economic value of impact through carbon emission
Security of supply	of Minimisation of exposure to fuel price instability. Analysis of security of supply in the event of severe weather disruption and availability of back up generation and/or grid connection. Analysis of type of waste and its severity on the environment.

5. Algorithms

Numerous approaches and algorithms for optimizing hybrid renewable energy systems have been surveyed [10-12], with a focus on improving the reliability and lowering the computational time of optimization models [13-16]. The most common sizing methodologies reported in the literature are graphical construction methods, probabilistic methods, analytical methods, iterative methods,

artificial-intelligence methods and hybrid methods. Probabilistic, analytical and iterative methods require continuity and differentiability of the equations describing the problem, resulting in CPU-intensive calculations, and are not suited to simulating dynamic performance or readily able to account for factors such as thermal constraints and component degradation over the life cycle. If optimization problems have high problem dimensions with several local optima, as is typically the case in a complex energy system, artificial-intelligence approaches such as heuristic optimization techniques are more favourable, as these methods are able to adequately account for dynamic performance and changing system variables with low average error [17]. The selection of an optimization technique ultimately depends on the adopted design criteria, available information, computing resources and the accuracy of the technique.

5.1. Hybrid artificial intelligence methods

In recent years it has become clear that combining an optimization algorithm with other optimization techniques to produce a hybrid (or metaheuristic) algorithm may lead to more efficient behavior and higher flexibility in solving a wide range of optimization problems. This is a complex methodology, but once implemented produces major savings in computation time and has developed into a significant research field [18].

Evolutionary algorithms are the basis of a common meta-heuristic optimization approach where the best solutions are isolated by eliminating the poorest solutions. Meta-heuristic algorithms include: Particle Swarm Optimization (PSO), which uses solutions that move in a design space based on their position [19] and Genetic Algorithm (GA), which uses a fixed linear data structure that allows hierarchical variables [20]. A recent review of optimization studies of renewable energy systems in the period 2013–2015 [21] found that GA (63%) and PSO (30%) were the most-used optimization techniques.

6. Discussion

Of reviewed optimization studies, refer Table 1 Ref. [22], a large majority of optimization assessments assess only techno-economic criteria. There is therefore an opportunity to change the basis of costing to become more comprehensive and thereby more honest, since in all cases the costs are paid somewhere.

Incorporating environmental and socio-political criteria is less straightforward and less certain than a performance- or cost-based assessment. As renewable energy systems become larger, the urgency to accurately predict the outcomes in terms of the selected design criteria will also grow, so that funding, time and public acceptance are not squandered through inappropriate configurations, capacities or locations.

The result of an optimization can only be as good as its inputs, but good inputs will be distorted by poor internal mathematical models. Accurate models of PV arrays are readily available. The stochastic element of wind energy poses a problem, but credible models are readily available. Likewise, battery models are readily available. The development of accurate but tractable electrolyser and fuel-cell models is more recent [13], but these have now reached the point of being both simple enough for incorporation in heuristic optimization and accurate enough to be credible. Hydrogen storage modelling is in a much less advanced state.

7. Conclusion

This paper advocates a more generalised approach to the optimisation of renewable energy storage systems which recognises that performance has different meaning in different contexts and so includes not just technical performance and cost factors, but also environmental and socio-political factors. These can be given weightings to produce an overall performance metric against which the system design is measured during optimisation.

8. Further study

Further studies are recommended into the implementation of a design methodology which takes into account a multi objective criteria whilst carrying out optimization of a system using genetic algorithm. This design methodology would be well placed for analyzing both grid and off grid small and large scale renewable systems.

A survey of modelling/simulation/optimization software packages showed that there is a need for new developments, specifically in modelling hydrogen storage, and generally in adopting a more flexible approach to shaping design criteria additional to cost and technical performance.

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