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# Multi-objective optimisation of renewable hybrid energy systems with desalination

Daniel P. Clarke*, Yasir M. Al-Abdeli, Ganesh Kothapalli

*School of Engineering, Edith Cowan University, Joondalup, WA 6027, Australia*

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The optimisation, sizing and techno-economic assessment of stand-alone renewable energy systems affects not only the likelihood of deployment but also their reliability to supply electricity and potable water where needed. Very little work has been done earlier into the effects of integrating water desalination alongside meeting load demand. Moreover, the impact of intelligent techniques, in this context, against more established software tools has not been applied. In this paper, PSO (Particle Swarm Optimisation) is compared to HOMER for the simultaneous optimisation of size and PMS (Power Management Strategy) in stand-alone hybrid energy systems. These systems incorporate significant relative water load met by reverse osmosis. Multi-objective functions in PSO minimise Total *NPC* (Net Present Cost) (includes capital, maintenance and replacement costs over a 25 year system lifetime) and lifetime $CO_2$ emissions whilst meeting these two loads. Results are analysed and compared for the conditions of dynamic (15 min resolved) versus static water demand in addition to meeting varying electric loads. The PSO algorithm is implemented using MATLAB/Simulink and compared to a similar overall configuration developed in HOMER to meet the same loads (electric, water).

Results show using PSO achieves systems having lower *NPC* compared to HOMER, with the margin of improvement more pronounced in greater scale systems as water storage capacity and electrical load increase. Additionally, having a time-varying water profile negatively effects system performance by increasing *NPC* and $CO_2$ emissions compared to a static water profile.

## 1. Introduction

With connection to the electrical grid very costly for remote locations, renewable energy is increasingly being integrated into stand-alone energy systems to reduce reliance on diesel power generation. Renewables (such as solar and wind) remain attractive as perpetual and secure long-term energy sources. As such, they are an excellent candidate for stand-alone power generation at reduced or negligible operational emissions [1]. However, renewable sources are highly stochastic and experience seasonal fluctuations [2]. Thus energy storage devices such as batteries and hydrogen are often used in stand-alone (hybrid) energy systems [3–6]. Energy storage is essential where there exists a mismatch between external electrical loads and the availability of renewables, and facilitates overall system operation by smoothing out load fluctuations [6] and improving operational characteristics [7].

Effective sizing of hybridised energy systems is necessary to achieve objectives such as meeting external load demand or reducing lifetime $CO_2$ footprint, whilst operating at the lowest energy cost ($/kWhr) [8,9]. The sizing of such systems commonly relies on “simplistically” matching peak demand with the maximum rated capacity of system components [10,11]. However, this approach has the likely outcome that systems are oversized which yields more costly solutions to meet a given electric load profile. More elaborate techniques attempt to optimise sizing through numerical methods, which can be iterative or probabilistic as well as based on genetic algorithms, fuzzy logic or neural networks [3,8,12–18]. Within this scope, PSO (Particle Swarm Optimisation) is an intelligent optimisation technique with many advantages such as fewer tuneable parameters and less dependence on the set of initial conditions, compared to some of the other intelligent techniques [19–21]. Additionally, the use of PSO has been shown to reduce environmental impact over a systems

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* Corresponding author. School of Engineering, Edith Cowan University, 270 Joondalup Drive, WA 6027, Australia. Tel.: +61 433 489 214.
*E-mail address:* daniel.clarke@ecu.edu.au (D.P. Clarke).

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lifetime by reducing $CO_2$ emissions [22]. Software tools such as HOMER (Hybrid Optimisation Model for Electric Renewables) developed by the National Renewable Energy Laboratory, NREL-USA) have also been applied to allow techno-economic sizing of micro-power hybrid systems [23–25] and are freely available [26]. However, whilst such software tools are accompanied with excellent Graphical User Interfaces (GUI's), they are largely used as "black boxes" with some limited ability to parameterise. They are also not self-adaptive nor capable of accounting for device transients such as start-up time or control set points (e.g. storage capacity thresholds), both of which affects system performance.

In relation to the optimisation of hydrogen systems, published literature largely focusses on the use of pre-defined (static) PMS (Power Management Strategies) [8,12,27–29] even when other intelligent methods have been used [16]. This occurs despite system-level inputs (renewables) are highly intermittent and outputs (electric load demand) also fluctuate. An effective PMS is critical in hybridised systems as both the reliability of meeting external loads as well as system performance are affected by the PMS architecture and the control set-points within it [30–32]. Specifically, an optimised PMS can result in reduced payback time [22], improved system reliability at the smallest total infrastructure cost [33–39], and reductions to the cost of energy ($/kWhr) over the system lifetime [35,40]. However, both the sizing of stand-alone energy systems and optimisation of their PMS typically needs to consider not only single objectives, such as minimising *NPC* (Net Present Cost), but multiple objectives which are economic, environmental or a combination of these three [41–43]. In this regard, multi-objective optimisation has targeted minimising the cost of energy by using different storage technologies [44], total hardware costs over the system's lifetime [29,45] and operational emissions [46,47], even though much of this research still encompasses diesel generation. Little research has been done to apply multi-objective optimisation to the PMS in renewably powered hybridised (hydrogen) energy systems designed to meet both electric load and desalinated water demand. Such elaborate optimisations are also beyond the scope of software tools such as HOMER because unlike PSO, such tools do not incorporate the dynamic characteristics of hardware components which is necessary to give system simulations the necessary realism as conditions fluctuate through the day.

Furthermore, few studies have attempted to compare the resulting performance gains when using PSO, in a multi-objective context to optimise both the PMS (Power Management Strategy) and component size, against widely adopted software optimisation tools such as HOMER. This type of research is worthwhile because for much lower levels of complexity (single objective function optimisations), the use of PSO compared to HOMER can decrease dependence on diesel generators by 10%, attain a lower *NPC* [39] and yield cost of energy improvements [48]. However, these earlier works have not accounted for the dynamic (time-resolved) operational characteristics of energy system components, have not considered systems which also sustain (small-scale) stand-alone desalination systems and have also overlooked the need to consider environmental impact ($CO_2$ emissions). This can be addressed through multi-objective optimisations like those covered by the present study.

This paper extends our preliminary work whereby PSO was used to optimise Power Management Strategies with only single objectives [32]. In the present research, optimisation of both energy system (component) sizing and the PMS is done for multiple objective functions, and then compared to HOMER. The stand-alone energy system considered in the present study is completely powered by renewables and must meet two external loads: (i) power generation (kWhr) and (ii) desalinated water generation (litres). The two objective functions used to guide the optimisation are: (i) minimising total Net Present Cost (*NPC*, $) and (ii) $CO_2$ emissions (kg/kWhr over a lifetime). The present research also studies the effects of dynamic, versus static, water demand as well as varying the scale of electric load and water storage capacity. A secondary aim of this research is to also study the effects of Power Management optimisations on device cyclability. The PSO algorithm is implemented using MATLAB/Simulink (v.8.3) and the simulations are performed on a desktop PC having an Intel i3 processor. The reader is referred to our earlier work for details of the PSO methodology [32] which uses the optimised acceleration parameters $c1 = 1.5$ and $c2 = 1$. Many of the energy system components, featuring in the simulations, have already been experimentally resolved through our earlier works [7,49]. Renewable data profiles for a specific coastal location (Geraldton, Western Australia) [50], having an abundant supply of salt water for RO (Reverse Osmosis), are utilised throughout.

## 2. Methodology

Fig. 1 presents the structure of the hybrid energy system which forms the focus of this study. Table 1 lists typical component data used in the simulations (cost components) for PV panels, PEM fuel cell(s), PEM electrolyser(s), DC/DC converter(s), metal hydride canister(s) [51] as well as lead-acid batteries [52], reverse osmosis unit(s) [53] and water storage tank(s) [54] with their associated $CO_2$ emission rate (kg $CO_2$-eq/kWhr) [46,55]. This data is specified per single unit, but the number of hardware units is derived through the optimisation.

### *2.1. Electrical sub-system*

This is responsible for converting solar energy to supply both the electrical load demand and other energy system components. Short-term energy storage (lead-acid batteries) are used for meeting daily demands while long-term storage (hydrogen) helps supplement battery capacity when seasonal or daily solar energy fluctuations mean short-term storage is insufficient to supply loads. Lead-acid batteries are used in the present research because of their lower capital costs compared to alternative technologies such as nickel–cadmium and Li-Ion [56]. Fig. 2 shows the normalised daily variation of power and water demand as well as solar irradiance over a year. Although the values plotted show daily totals, this is derived using 15 min resolved data which itself is used in the simulations. In these simulations, both external power and water demand is also scaled (up/down) to help analyse the effects of scalability. Cumulative power demand is scaled such that averaged daily demand over an entire year is at three levels (1.5, 2.5 and 3.5 kWhr/day). Although the annual water required is kept fixed at 146 kL/yr, the simulation also consider the impact of assuming a uniformly distributed equivalent daily rate (400 L/day over 365 days) versus a time-varying water profile as depicted in Fig. 2. Furthermore, to satisfy this external water demand, the required power is approximately 3–6 times that of the external electric load.

### *2.2. Desalination sub-system*

This incorporates RO units plus water storage tanks designated through their max storage capacity ($H_2O_{max}$) and is responsible for supplying potable (drinking) water as well as electrolysis, whereby water is deionised using non-power consuming static cartridges. The values for $H_2O_{max}$ are either 2 kL or 20 kL in the simulations. Whilst many desalination techniques exist (multistage flash, vapour compression and electro dialysis [57]), RO is chosen because it is the most commonly integrated (non-thermal) desalination technique in renewable energy systems [15,58–60]. Reverse