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DOES THE INCLUSION OF A HYDROGEN-BASED ENERGY SYSTEM IMPROVES THE ROBUSTNESS OF THE LEVELIZED COST OF ELECTRICITY FOR AN URBAN, GRID-CONNECTED HOUSEHOLD?

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ABSTRACT

Hydrogen-based energy systems are a viable solution to perform long-term storage of excess intermittent renewable energy. However, such systems are rarely considered in energy system optimization. Moreover, whenever these technologies are considered, the model parameters are considered known and fixed, which can result in suboptimal designs, sensitive to uncertainty. To evaluate the inclusion of a hydrogen-based system in a global energy system and to address the uncertainty on its techno-economic performance, we performed an optimization under uncertainty of a solar-powered, grid-connected household, supported by batteries and hydrogen storage. This paper illustrates the effect of the hydrogen-based energy system on the uncertainty of the predicted levelized cost of electricity. The inclusion of the hydrogen system decreases the standard deviation of the levelized cost of electricity by 4.3 €/MWh (13%) at the expense of an increase in mean levelized cost of electricity by 100 €/MWh (28%). Consequently, despite the gain in robustness, including a hydrogen-based storage system in the considered urban area is not beneficial overall. Future works will focus on including remote areas, to fully exploit the gain in robustness induced by hydrogen-based storage systems.

Keywords: hydrogen-based energy system, levelized cost of electricity, uncertainty, robust design optimization.

1. INTRODUCTION

To match intermittent renewable energy supply with energy demand, renewable energy systems (e.g. PhotoVoltaic (PV) system and wind turbines) are coupled with energy storage technologies (e.g. battery, hydrogen storage). In such a Hybrid Renewable Energy System (HRES) configuration, a battery system is suitable to cover short-term energy storage (<week), while hydrogen-based energy storage covers longer periods (>months) [1]. Despite the advantage of including a hydrogen-based energy system in an HRES, these technologies are rarely considered in techno-economic design optimization of global energy systems [2]. In such design optimization studies of HRES, technical and economic parameter values are assumed deterministic (i.e. known and fixed). However, during the planning, construction and operation stage of the system, such parameters are subject to real-world uncertainties [3]. To address the effect of these uncertainties on the system performance, Robust Design Optimization (RDO) considers uncertainties on these system parameters and provides robust designs that are least sensitive to these inherent parameter variations [4-6]. Despite the clear importance of considering uncertainties in design optimization, its application to accurate renewable energy system models is minimal, as the stochastic evaluation of such complex models becomes computationally intractable when more than a handful of uncertain parameters are considered (>10 parameters) [7].

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To characterize the effect of a hydrogen-based energy system on the Levelized Cost Of Electricity (LCOE) of an urban, grid-connected household, we developed a non-linear, techno-economic system model of a hydrogen-based HRES. Moreover, we considered the uncertainty on 43 technical and economic model parameters to characterize the impact of the inherent variability of these parameters during real-life operation, and we performed a computationally efficient RDO to provide a robust design that is least-sensitive to this uncertainty. Finally, we compared this robust design with the deterministic design and with designs from the literature. In section 2, the system and stochastic optimization algorithm is described, followed by the results in section 3 and the conclusion in section 4.

2. METHOD

In this section, we describe the HRES and the adopted models, followed by the location-specific data considered and the design optimization algorithms applied.

2.1 System description and modelling

In this work, we considered a grid-connected household with a PV array to provide electricity from solar energy. To store an excess of solar energy, a hybrid storage system is implemented, consisting of Li-ion batteries and pressurized (30 bar [8]) Proton Exchange Membrane (PEM) electrolyzers with hydrogen storage tank. To recover the electricity stored in the form of hydrogen, a PEM fuel cell array is connected to the hydrogen storage tank. To ensure an optimal cooperation between the different energy suppliers (i.e. grid, PV array and PEM fuel cell array) and storage systems (batteries and PEM electrolyzer with hydrogen storage tank), the following energy management strategy is applied [9]: The electricity produced by the PV array is directly used to cover the energy demand. When the PV does not meet the demand at a specific time, the energy available in the batteries is consumed, followed by the hydrogen power system and finally the grid. When the PV array produces power above the household demand, the batteries are first charged, followed by hydrogen production in the PEM electrolyzer array. In this work, no grid injection is considered.

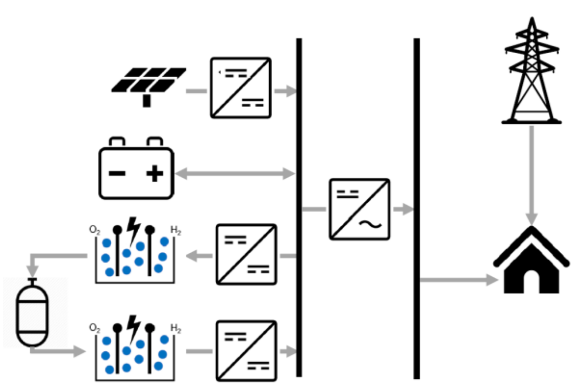

Fig 1 The grid-connected household is supported by a photovoltaic array to cover the electricity demand. To store the excess electricity, a battery array and hydrogen-based energy system, consisting of electrolyzer, storage tank and fuel cell, are considered.

We modelled each component individually and combined these models in a general system model developed in Python. The PV model is adopted from the PVLib Python library [10], where we selected the 80 Wp Canadian Solar CS5C-80M module. We considered the PEM electrolyzer and fuel cell models developed in [11], while the hydrogen tank model and the battery model was adopted from [12]. To determine the techno-economic performance of the system in an urban area, we considered Brussels (Belgium) as location. We adopted the hourly solar irradiance and ambient temperature data from [13], which are based on a Typical Meteorological Year. On the demand side, we considered the load profile provided by [14]. Based on the method presented by Montero et al [15], the data was adjusted to construct a location-specific load profile. We adopted the grid price from predictions of the Belgian transmission system operator Elia [16].

2.2 Design optimization

To determine the location-specific optimal designs, we considered 5 design parameters: the number of PV panels, PEM electrolyzers, PEM fuel cells, the battery size and hydrogen tank volume. The techno-economic performance of the system designs is characterized by the LCOE.

In total, 43 input parameters are considered uncertain (see Appendix for complete list). The uncertainty on the economic parameters is based on uncertainty in future technology evolution and bulk manufacturing size of the components. The list of uncertain parameters includes the grid price and, for each component (i.e. PV panels, PEM electrolyzer, hydrogen storage tank, PEM fuel cell, battery, DC-DC converter, DC-AC inverter), the specific capital expenditure, specific operational expenditure, specific replacement cost and lifetime. To represent the technical uncertainties of the system, the membrane area, membrane thickness, pressure and temperature in the PEM electrolyzer and fuel cell are considered uncertain, as well as the inverter, converter and battery efficiency, self-discharge rate of the battery and the power production of the PV panels. For each of these parameters, we considered a Gaussian probability density function.

To propagate the uncertainties through the system and quantify the statistical moments (i.e. mean and standard deviation) of the LCOE, we applied a robust and computationally efficient sparse Polynomial Chaos Expansion (PCE) technique [7]. By combining the sparse PCE with a genetic algorithm, the mean and standard deviation are evaluated for each design sample by PCE and these objectives are consequently optimized via the genetic algorithm [4]. By reducing the standard deviation of the LCOE, the probability of the mean representing the real-life performance increases. Therefore, a robust design that achieves the minimum standard deviation for the objective, ensures the highest probability of performing near the mean. Consequently, a design that significantly reduces the standard deviation, at the expense of a marginal worsening of the mean, is more beneficial overall than the optimal mean design.

3. RESULTS AND DISCUSSION

When uncertainties are considered and the RDO algorithm is applied to the system, the configuration achieving the minimum mean LCOE reaches a value below the expected mean grid cost (360 €/MWh as opposed to the projected mean grid price of 370 €/MWh) (Fig 2). This HRES configuration should consist of 12 PV panels and a 0.24 kWh battery system and covers 29% of the total annual electricity demand of the household (the grid covers the remaining 71%). An intermediate configuration reduces the standard deviation by 2.2 €/MWh at the expense of increasing the mean by 9 €/MWh. This configuration consists of 22 PV panels, a 0.24 kWh battery system and no hydrogen-based energy system components. The robust HRES design however, consists of 33 PV panels, 7 electrolyzers, 16 fuel cells and a 0.1 m^3 (8.5 kWh) hydrogen tank. By introducing the hydrogen-based energy system, the coverage of the total annual electricity demand is increased up to 45% absolute and the standard deviation of the LCOE is reduced by 4.3 €/MWh, at the expense of an increase in mean LCOE by 100 €/MWh compared to the optimal mean design. Consequently, including a hydrogen-based energy system increases the grid independence from the grid and improves the LCOE robustness. However, the increase in mean LCOE is large compared to the gain in robustness. Therefore, despite the gain in robustness, including a hydrogen-based energy system in the considered urban area is not considered beneficial overall.

When further decreasing the grid dependency, the mean LCOE increases exponentially (Fig 3). To achieve a further reduction of the grid dependency, the HRES capacity should increase, resulting in a rapid increase in investment and replacement costs of the PV array, battery system and hydrogen-based energy system[1]. Consequently, the standard deviation of the LCOE increases proportionally with the HRES capacity installed. Therefore, since the uncertainty on the future electricity price from the grid is moderate in the considered urbanized location, the standard deviation does not further decrease when further increasing the

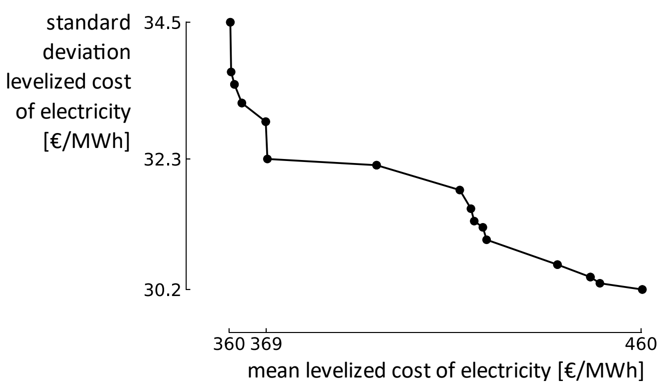

Fig 2 A trade-off exists between minimizing the mean levelized cost of electricity and minimizing its standard deviation. The decrease in standard deviation (4.3 €/MWh) is however small compared to the total increase in mean levelized cost of electricity (100 €/MWh).

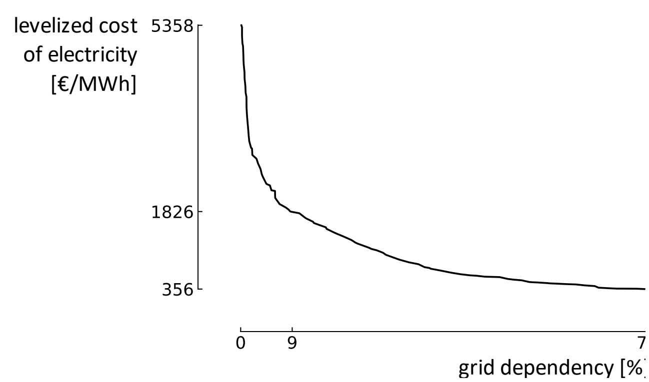

Fig 3 The levelized cost is optimal when 71% of the total annual electricity demand is covered by the grid. When decrease the grid dependency, the levelized cost increases exponentially.

[1] To fully cover the electricity demand with the HRES (i.e. autonomous system), the HRES should consist of 1242 PV panels, 101 electrolyzers and 90 fuel cells, supported by a pressurized hydrogen tank of 0.77 m^3 (66.2 kWh) and a 7.77 kWh battery system.

share of electricity demand covered by the HRES above 45%.

4. CONCLUSION

The introduction of hydrogen-based energy systems in a global energy system is a viable solution to comply with long-term (i.e. months) energy storage. For grid-connected households, an inclusion of such a system affects the levelized cost of electricity. The robust design for such a system, consisting of 33 PV panels, 7 electrolyzers, 16 fuel cells, a 0.1 m^3 (8.5 kWh) hydrogen tank and 0.24 kWh battery system, decreases the standard deviation of the levelized cost of electricity by 4.3 €/MWh, at the expense of a 100 €/MWh increase in its mean. Therefore, the inclusion of a hydrogen-based energy system improves the techno-economic performance robustness, even in an urban location with only a moderate uncertainty on the grid price. However, despite the gain in robustness, including a hydrogen-based energy system in the considered urban area is not beneficial overall. During future works, we will compare different locations, including locations with larger uncertainties on future grid price (i.e. remote locations), to fully exploit the advantage of increasing the robustness with hydrogen-based storage.

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APPENDIX

Table A Model parameter ranges

Parameter	range
Solar irradiance	± 3.8% [17]
Ambient temperature	± 1 K [18]
Load	± 20% [19]
Grid price	370 ± 141 €/MWh [16]
$CAPEX_{PV}$	780 ± 520 €/kW_p [20]
$OPEX_{PV}$	17.5 ± 1.5 €/kW_p [20]
$lifetime_{PV}$	22.5 ± 2.5 year [21]
Power $output_{PV}$	± 5 W [22]
$CAPEX_{electrolyzer}$	1750 ± 350 €/kW [23]
$OPEX_{electrolyzer}$	4 ± 1% [23]
$Lifetime_{electrolyzer}$	80000 ± 20000 h [23]
Replacement $cost_{electrolyzer}$	0.275 ± 0.025% [23]
Membrane $area_{electrolyzer}$	50 ± 1 cm^2 [11]
Membrane $thickness_{electrolyzer}$	50 ± 1 µm [11]
$Temperature_{electrolyzer}$	353 ± 1 K [11]
$Pressure_{electrolyzer}$	30 ± 0.1 bar [11]
$CAPEX_{tank}$	522.5 ± 102.5 €/kg [24,25]
$OPEX_{tank}$	1 ± 1% [25,26]
$Lifetime_{tank}$	22.5 ± 2.5 year [26]
$CAPEX_{fuel\ cell}$	2765 ± 495 €/kW [27]
$OPEX_{fuel\ cell}$	95 ± 15 €/kW [27]
Replacement $cost_{fuel\ cell}$	730 ± 70 €/kW [27]
$Lifetime_{fuel\ cell}$	25000 ± 5000 h [26]
Membrane $area_{fuel\ cell}$	50 ± 1 cm^2 [11]
Membrane $thickness_{fuel\ cell}$	178 ± 1 µm [11]
$Temperature_{fuel\ cell}$	353 ± 1 K [11]
$Pressure_{fuel\ cell}$	1.2 ± 0.1 bar [11]
$CAPEX_{bat}$	844 ± 342 €/kWh [28]
$OPEX_{bat}$	8.05 ± 3.15 €/kWh [29]
$Lifetime_{bat}$	10250 ± 5500 cycles [28]
Replacement $cost_{bat}$	394.5 ± 110.5 €/kWh [29]
$Efficiency_{bat}$	90 ± 5% [28,29]
Self discharge $rate_{bat}$	0.2 ± 0.1 %/day [29]
$CAPEX_{DC-DC}$	245 ± 35 €/kW [30]
$OPEX_{DC-DC}$	1 ± 1% [31,32]
$lifetime_{DC-DC}$	17.5 ± 7.5 year [33]
$efficiency_{DC-DC}$	90 ± 1% [31,32]
$CAPEX_{DC-AC}$	461 ± 187 €/kW [33]
$OPEX_{DC-AC}$	3 ± 2% [28,29]
Replacement $cost_{DC-AC}$	257 ± 174 year [28,29]
$lifetime_{DC-AC}$	17.5 ± 7.5 year [33]
$efficiency_{DC-AC}$	95.25 ± 1.25% [33]