An uncertainty and sensitivity analysis of Power-to-Hydrogen as a seasonal storage option in a district multi-energy system

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Abstract.
Seasonal energy storage plays a key role in low-carbon multi-energy systems (MES) by storing renewable generation in times of excess supply in order to meet energy demands months in the future. Power-to-Hydrogen (PtH2) is being investigated as a promising long-term storage solution for integrated MES. In this preliminary work we investigate under which conditions does PtH2 become a seasonal storage option in district MES through an optimization framework including an uncertainty and sensitivity analysis to evaluate the effect of technological and contextual uncertainty on PtH2 execution. PtH2 becomes vital in low-carbon, renewable-heavy, MES for meeting high thermal demands in winter.

Keywords: Power-to-Hydrogen, Seasonal storage, Multi-energy systems, Investment planning, Renewable energy sources, Storage technologies

1. Introduction
Multi-energy systems (MES) allow for district-size energy systems through the interaction of energy carriers (e.g. electricity, heat, natural gas, and Hydrogen (H2)), creating new value propositions for increased reliability, lower carbon footprints, and improved economics [1, 2]. Many point to the necessity of seasonal energy storage to time-shift a significant amount of intermittent renewable energy production for non-dispatchable loads [3, 5, 7].

Only a few technologies are capable of seasonal storage without significant self-discharge (e.g. electrochemical batteries such as Lithium-ion) which would negate their technical and economic ability to store energy long-term. The most feasible incumbent seasonal energy storage technology has been pumped hydroelectric storage. Unfortunately, it is geographically dependent and difficult to permit for environmental reasons, requiring either mountain valleys or used mines. An emerging technology called Power-to-Hydrogen (PtH2), coupled with large thermal storage (e.g. hot water sensible thermal storage), has been recognized as a promising seasonal storage option in district MES through an optimization framework including an uncertainty and sensitivity analysis to evaluate the effect of technological and contextual uncertainty on PtH2 execution.
storage method capable of offsetting variations in renewable generation at the district-scale [6, 7]. PtH₂ includes fuel cells, electrolyzers, and H₂ compressed storage tanks as the chief technologies.

Quantitative energy modeling with optimization provides the ability to design functional MES in a least-cost and least-emissions manner [4, 8]. Many models and tools are challenged by the computational effort involved in optimal design and operation of such complex systems due to the large number of decision variables over the required time horizon [4, 9]. This makes it more difficult to incorporate techno-economic uncertainties to develop robust MES designs.

Uncertainty analysis entails the characterization of the uncertain model parameters and the assignment of an appropriate mathematical representation to their uncertainty [10]. Employing the uncertain stochastic nature of each technology (i.e. cost, efficiency, lifetime, etc.) and context (i.e. electricity price, grid carbon intensity, renewable feed-in-tariffs, etc.) parameters provides a more robust design rather than deterministically describing each parameter with one value, which could possibly lead to suboptimal MES configurations.

The uncertainty investigation approach chosen for the purpose of this work consists of a detailed uncertainty characterization (UC) allowing for a local sensitivity analysis (LSA) and Monte Carlo (MC) simulations over various conditions, which together allow to assess the performance of the MES design under uncertainty. In this work we use the MES optimization model demonstrated in [4]. The novelty of this contribution is that the whole set of uncertain economic and technical input parameters are considered to answer the question - under which conditions does PtH₂ become a seasonal storage option in a district multi-energy system?

2. System description and optimization problem

The MES is connected to the NG and electricity grids and consists of a set of conversion and storage technologies including solar PV panels, electricity-driven air heat pump (edHP), natural gas boiler, WTs, hot water sensible thermal storage (HWTS), Lithium-ion battery (LiB), and the Power-to-Hydrogen (PtH₂) system, as demonstrated in (Figure 1). The PtH₂ system consists of a proton exchange membrane electrolyzer (PEMEC), an air-sourced PEM fuel cell (PEMFC), and a H₂ storage tank (H₂S). Of the four energy carriers considered here, electricity can be imported / exported, gas solely imported, with heat and H₂ remaining within the MES topology, with no network models considered as this is modeled as a centralized district energy hub.

2.1. System description

The model uses an hourly resolution for all input data and decision variables. The problem is formulated as a deterministic mixed integer linear program (MILP) to determine the selection, size, and operation of the considered conversion and storage technologies that minimize the total annual cost, and / or the CO₂ emissions, of the system. It is written generally as:

\[
\min_{x,y} \ (c^T x + d^T y) \quad (1)
\]

\[
s.t. \quad Ax + By = b
\]

\[
x \geq 0 \in \mathbb{R}^{N_x}, y \in \{0, 1\}^{N_y}
\]

where \( x \) and \( y \) represent the continuous and binary decision variables with the corresponding cost vectors \( c \) and \( d \), and constraint matrices \( A \), \( B \) and \( b \) is the constraint known-term; \( N_x \) and \( N_y \) indicate the dimension of \( x \) and \( y \), respectively [4]. \( T \) indicates the number of time instants in the time horizon; as data are available at every hour of the year, \( T = 8760 \). In the following, the optimization problem is further described in terms of input data, decision variables, constraints, and objective function. More detailed descriptions of such features can be found in the original
model development in Gabrielli et al. [3, 4]. The objective of the optimization problem can be set either to total annual costs (annualized capital and operational costs) or annual emissions.

The deterministic input data include the specific locations’ weather conditions such as air temperature, wind speed, solar irradiation, along with the district energy demands. Uncertain parameters are identified through a UC for all technologies, with their appropriate probabilistic distributions assigned. The district is modeled in the Dfc Köppen-Geiger climate zone with weather and renewable potential data from Bergen, Norway [11, 12]. District energy demands were synthesized based on various proportions of residential, commercial, and baseload profiles from the U.S. Department of Energy (DOE) Building Technologies program database [13].

2.2. Uncertainty characterization
The UC encompasses the identification of the uncertain model parameters and the attribution of probabilistic descriptions to their uncertainty [14]. Two probability distributions are considered: the uniform and the PERT distribution [15]. The context parameters considered for the UC include energy carrier prices (electricity and NG), grid CO₂ intensity, FiT, and discount rate which are taken as the European averages respectively [14, 16]. The CO₂ tax of 90 EUR/T CO₂ is not taken into account as it will be studied through the MC simulations. The technologies applied in the optimization problem show a high degree of variance in technological and economic data when comparing different literature sources [15], which are not shown in this work.

2.3. Local Sensitivity analysis
Based on this optimization framework, an LSA is performed to determine the most sensitive input parameters over the three objectives. In the sensitivity analysis, variation is created by

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2 Renewables.ninja (www.renewables.ninja) provides geolocated renewable potentials available under the Creative Commons Attribution Non-Commercial 4.0 International (CC BY-NC 4.0) license.

3 Open-source data from the U.S. DOE BT program is available on OpenEI.
changing every input factor by ±20% and comparing the results with the base case. For every change in input parameter, a cost, emission, and cost optimization with an emissions limit is performed. This limit is chosen based on an analysis of each district’s Pareto front to find the sensitivities at an emissions limit with the first execution of PtH2.

2.4. Monte Carlo simulation

The MC analyses are done over three objectives:

i. Cost objective

ii. Emissions objective (excluding CO2 tax)

iii. Cost objective with uncertain probability distribution of the CO2 tax

Whenever the nature of uncertainty is stochastic, Mathematical Programming and MC can be combined [17]. Considering the large number of uncertain input parameters and the computation intensity of our optimization model, we set the number of iterations of each case to 1000. In every iteration a random set of input parameters is generated, considering the probability distribution of each parameter. The optimization problem is then solved and decision variables recorded. A distribution of the system configuration, total annual cost and emissions are generated, allowing decision makers can estimate how the objective function varies considering uncertainty.

3. Results

A base case cost-emission Pareto front is analyzed in Figure 2. The Pareto front shows significant negative operational costs at every point except the cost scenario, due to large installations of renewables utilizing the FIT for grid export expressed with the solar PV and WT execution. A large amount of renewables are built to meet the high energy demands in winter when there is lower solar irradiation, necessitating PtH2 systems in scenarios under emissions of 60 gCO2/kWh with an example stored energy (HWTS, battery, and H2S) over the year in Figure 4. Interestingly, in nearly all scenarios, WT electricity is exported nearly year-round while solar PV only in the summer, with large renewable production is self-consumed in the winter.
Figure 3. LSA for ±20% with a cost objective with (right) and without (left) an emissions cap.

3.1. Local sensitivity analysis

Figure 3 shows the most sensitive parameters on cost objectives with and without a CO₂ cap.

Cost optimization

Independent of which input parameter is changed for the cost objective, the energy demand is always covered using a heat pump, boiler, HWTS, some solar PV along with electricity and gas imports, with large amounts of WTs installed. The solar PV, boiler, HWTS, and WTs show variation in the installed size in most significant sensitive parameters shown in Figure 3. The most significant technological parameters in the cost objective are the WT capital cost, boiler efficiency, and WT lifetime, while the significant context parameters are the FiT, NG price, and discount rate. The WT capital cost, WT lifetime, FiT, and discount rate proportionately scale the execution of WT between 1 and 21 units (1,500 kW and 31,500 kW), with 5 (7,500 kW) being the base case. Surprisingly, the edHP sees no variation in any of the LSA runs. The WT capital cost and FiT seem one-sided due to the higher reliance on the grid in the smaller sensitivity levels. Overall, this demonstrates the high reliance on WTs due to the large wind resource compared to solar irradiation. Due to the high autarky (over 1), the electricity price does not significantly impact the system. No storage systems except HWTS are installed.

Emission optimization

An emission optimal base case district MES has, on average, a total cost that is 25 times higher than a cost optimal MES, with 21 times lower emissions. The district always uses the maximum technology sizing except for the boiler, HWTS, and the WT which vary in the most sensitive designs. The upper limit of battery and PtH₂ technologies are reached in every sample, with reliance on the boiler even in the emissions scenario required to meet high winter thermal loads. The most sensitive parameters are the storage technologies’ efficiencies, demonstrating the high dependence of short-term and seasonal storage in low-emissions energy systems. Grid CO₂ intensity does not play a large role due to the high autarkies of the system, but this would likely be a highly sensitive parameter in a grid-reliant system.

Cost optimization with an emission limit

PtH₂ systems are executed in each design, representing 9.3% of the districts’ maximum thermal load (0.02% of its annual energy demand) in the base case. Surprisingly, the district does not execute batteries. This has implications for chosen seasonal storage technologies depending on the climate zone and renewable availability. The district implements solar PV and WTs, with expected reliance on WTs. The most sensitive parameters are the boiler efficiency, WT capital cost, PEMFC overall efficiency, along with the discount rate and FiT. These parameters
Table 1. 95% cost and emission range of Monte Carlo simulations.

|                      | Mean cost [EUR / kWh] | 95% cost range            | Mean emissions [gCO₂/kWh] | 95% emission range       |
|----------------------|-----------------------|---------------------------|---------------------------|--------------------------|
| Cost obj.            | 0.021                 | [0.017 — 0.023]           | 128.4                     | [122.7 — 134.1]          |
| Emission obj.        | 0.378                 | [0.364 — 0.391]           | 0                         | [0 — 0]                  |
| Cost obj. CO₂ tax    | 0.019                 | [0.015 — 0.023]           | 55.7                      | [52.7 — 58.6]            |

Figure 4. Example stored energy in the H₂ storage, HWTS, and battery (left) and frequency of total costs and emissions for the MC simulations (right).

are in a different order of sensitivity compared to the cost objective due to the higher need for low-carbon heating sources, shown in its maximum execution of heat pumps.

3.2. Monte Carlo simulation
As shown in Figure 4 and Table 3.1 there are large cost and emissions variations between the two cost objectives (with and without CO₂ tax) and the emissions objective, which sees much higher costs but can accomplish 0 emissions. For the cost objectives, we see similar annual costs and technology executions, but a much lower range of emissions for the CO₂ scenario, demonstrating its significance. We see slightly lower system costs along with halved emissions in the cost with CO₂ tax objective. Neither the total annual costs nor emissions of the cost objectives are symmetrically distributed, with some systems having negative costs. Such systems are correlated with the nearly 0 emissions systems, typically with high WT installations mainly due to high sampled FiTs. Compared to the base case cost figures in the Pareto front, we see much lower average emissions (123 vs. 232 gCO₂/kWh) and costs (0.017 vs 0.057 /kWh), although still within the 95% confidence range. The total cost of an emission optimization is well distributed around a value 21 times higher than the total cost of a cost optimization, whereas the emissions are reduced to 0. The total costs show a longer tail towards lower values.

PtH₂ does not become an option except in the emissions scenario. Interestingly, the PtH₂ system is used in 89.5% of all emissions scenario cases, with PEMFC size ranges between 499 and 564 kW (PEMEC slightly bigger). The H₂S storage does not reach its maximum non-limiting amount, with a mean size of 262,000 kWh (corresponding to 0.05% of total annual demand).
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