Hydrogen Uncertainty Exploration: Initial Formulation and Test Run

Tom Bearpark

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1 Project Description

Many countries are considering whether to invest in hydrogen storage, as part of a future low carbon energy system. However, the usefulness of hydrogen storage to a future energy system depends on a number of unknown parameters. These include; the capital costs of electrolyser investment, the efficiency of converting power to hydrogen and back again, and the level of a future carbon tax.

My project aims to systematically analyse these uncertainties. I will do so by running an optimal power planning model for different combinations of carbon tax and hydrogen cost parameters. This will allow me to identify the set of hydrogen cost/carbon tax parameter combinations that imply that hydrogen investment brings cost savings to the system I am analysing.

To do so, I am using a detailed capacity expansion model, without unit commitment constraints. My study setting is the Electricity Reliability Corporation of Texas (ERCOT) system[1], and I am considering a brownfield capacity expansion planning study. My model runs use 52 weeks of data, which is necessary to capture the (potentially) long term[2] seasonal storage value of hydrogen.

2 Test system and data description

In my study, I add hydrogen storage and electrolyser investment as extra decision variables to the ERCOT capacity planning model presented in Notebook 07. Hydrogen is coded into my system as a storage decision variable, in the same way that batteries are coded in Notebook 07. I also implement a carbon tax, as discussed in Homework 05. I then vary key hydrogen cost parameters, and the carbon tax, and compare model outputs across these runs.

In order to add hydrogen and a carbon tax to the ERCOT 3 node capacity planning model, I need estimates of the parameters described in this section[3]. In my project, I will vary electrolyser CAPEX, hydrogen round trip efficiency, and carbon taxes across model runs. I plan to keep all other parameters fixed across model runs (except in sensitivity checks in the appendix).

H2 Fixed Investment Costs per MW-year

This variable corresponds to the investment costs of an electrolyser, which is a technology used for converting power into hydrogen. Annualised investment costs per MW can be calculated as a function of the lifetime of a plant (n), the Weighted Average Cost of Capital (i), and the Capex per MW ($CAPEX$) using the following formula...

$$\text{H2 Fixed Investment Costs per MW year } = CRF \times CAPEX = \frac{i(1+i)^n}{(1+i)^n - 1} \times CAPEX$$

In principle, I could run vary all of the inputs to this formula. However, in order to limit the complexity of my search, I will consider i and n as fixed, and vary $CAPEX$ across model runs. Since i and n only affect the optimal planning decision through this investment cost variable in my model formulation, we can interpret a model run for a given value of H2 fixed investment cost as being for a particular combination of the above variables without loss of generality of interpretation.

In my initial model runs, I have used the following values of these three variables:

[1] Data is provided by Professor Jenkins at the following link: `https://github.com/east-winds/power-systems-optimization/tree/master/Project/ercot_brownfield_expansion`

[2] My initial results show this to be important; hydrogen is used as a seasonal storage medium that converts power to hydrogen during the summer and turns it back during the winter.

[3] Please note, all of these are parameter values and ranges described below are preliminary.

Parameter	Unit	Values	Sources
n	Years	20	PyPSA WHOBS and Bareiß et al. 2019 Applied Energy Paper
i	Percent	0.069	From Power Genome. More reseach on this value is warranted.
$CAPEX$	$ per MW	{200, 500, 800}	Minimum value taken from Bloomberg New Energy Futures slides. Maximum value from here.

H2 Fixed O and M Costs per MW-year

Following p18 of this reference, I assume these to be 5% of the fixed investment costs. Since this cost is relatively small compared to the other hydrogen costs at play, I decided not to include this cost in my uncertainty search space, and leave it fixed across model runs. I will explore the sensitivity of my results to this assumption if I have time, in my appendix.

H2 Variable O and M Costs per MWh

I follow the approach taken by Notebook 07 for battery storage, and assume this to be zero. Note, this assumes away some important features of hydrogen production, including water costs. I abstract from this in my project by considering those costs as part of the efficiency parameter, which I describe below.

H2 Storage Investment Cost per MWh-year

I calculate this as a function of Capex, N, and the WACC, using the same formula as above. I use the same value of WACC as before. I assume Capex to be 0.6$ per Mwh, following this reference which is also used by PyPSA. I assume N = 40, which is the same as that used by PyPSA. Given the low relative value of this cost, I decided not to search across this value as part of the uncertainty space. However, if I have time, I will do some sensitivity analysis on this assumption.

H2 Storage Variable O and M Costs per MWh-year

I take the same approach to this variable as I did for the O and M costs for the electrolyser, and assume that it is zero.

H2 Efficiency of charge and discharge

This is a key parameter in hydrogen uncertainty analysis. Many papers have noted that low round trip efficiency drives the high expected costs of hydrogen investment. My initial model runs varied this parameter between 0.75 and 0.85. The low end estimate are taken from the most extreme values of Table 1 of this reference. I plan to review more literature over the coming weeks, in order make sure I am capturing a wide range of uncertainty.

Carbon tax

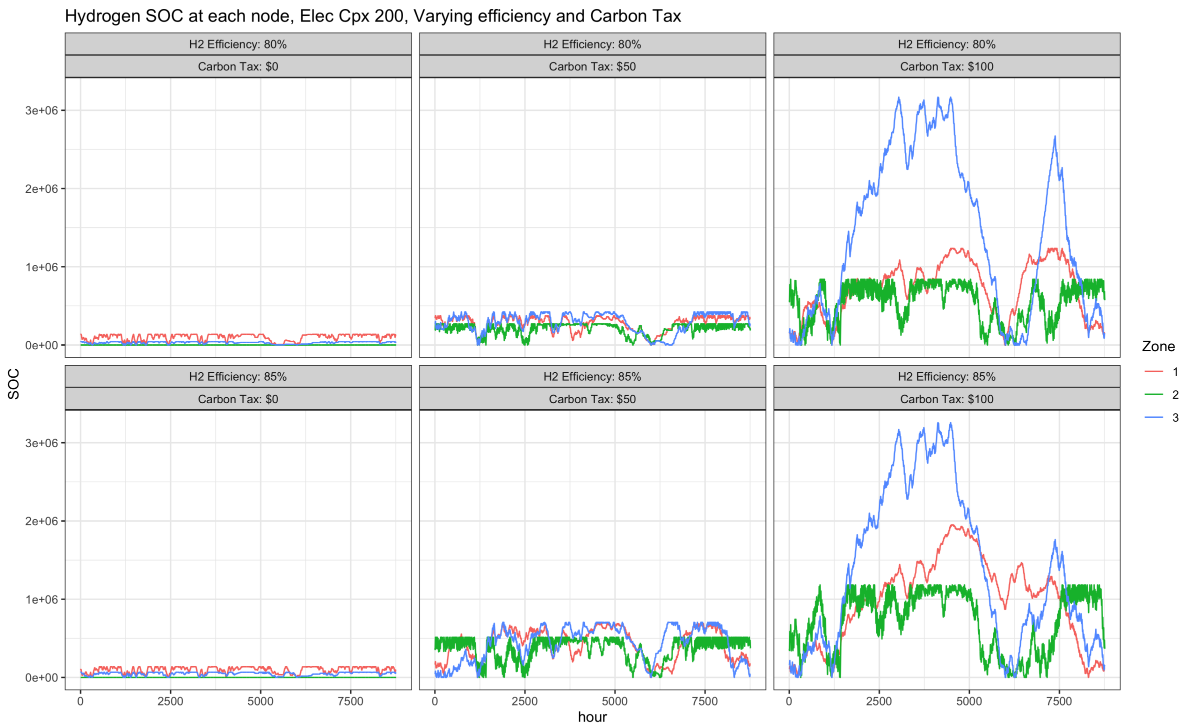
Academic estimates of the optimal future carbon tax vary widely, and the highly political nature of such a policy means that expectations of its future value can fluctuate rapidly. So far, I have conducted model runs under three carbon tax scenarios: $0, $50 and $100 per tonne. The low value is a lower bound. The $50 represents a reasonable expectation (the Obama EPA value was around $42 per tonne, so adjusting this for inflation and changes in climate expectations I obtained a rough value of $50 for a central scenario). The $100 value represents a high extreme. I believe that more granularity of search on this variable is warranted, and I am in the process of finding a systematic way of determining which values to search over.

3 Initial Results

Initial results for the runs that I have already completed can be found in the `/results/` folder of this submission. Please note, I have not plotted visuals or systematically explored all of these results so far, and I also plan to run a lot more scenarios than I have completed so far.

For the purposes of this submission, I have produced the below plot as a case study of my initial results. The below plot shows State of Charge for the hydrogen capacity built at each Zone, in six of the scenarios that I have run so far.

All of these scenarios have the same assumption ($200 per MW) on Capex. The first row of plots have a H2 efficiency of 80%, whilst the second row have an efficiency of 85%. Each column has a different level of carbon tax, indicated in the plot titles.



We can see that for high carbon taxes, hydrogen is used as seasonal storage. We also see that at low carbon taxes, there is very little investment in hydrogen technology. I am somewhat surprised at the second peak in hydrogen SOC in Zone 3 in the high carbon tax scenarios, and will investigate this further.

4 Discussion

Unexpected Difficulties

My main unexpected difficulty so far has been computational burden. At high levels of carbon tax, with cheap and relatively efficient storage, the model can take more than three hours to solve. I can limit the effect of this problem by running up to around 8 model runs simultaneously in parallel[4], and leaving the model to run on my laptop over night. I am considering options for reducing the computational burden - for example by implementing a time sampling approach designed for long duration storage (Kotzer et al 2018), or by running the model on 2 hour chunks instead of hourly chunks, but haven't yet implemented either of those techniques.

Another difficulty has been in trying to limit the dimensionality of my parameter search. There are many potential ways to vary the costs of hydrogen in this system, however, I only wanted to vary a few parameters in my search space, to allow for results that are interpretable for policy making. Therefore, I decided to vary the parameters that appeared in the literature to be the subject of the largest uncertainty, and to be the biggest determinants of future hydrogen system value.

Next steps

My next steps will focus on...

[4] To implement this, I used a bash script to loop over model runs and send out jobs to different processes on my laptop. See the code `/run_project.sh` for details. This would be very easy to put on a server - which would allow for a lot more parallel runs. I am currently exploring using Princeton's Adroit server for this purpose.

- Analysing the results that my model has produced so far. This process will include systematically analysing how hydrogen investment varies with the parameters I am varying, and producing tables and visualisations of outputs.
- Running all model runs defined by the parameter space I have discussed in this write up. This will give me 27 model runs in total (3 carbon tax levels * 3 Electrolyser Capex costs * 3 efficiency scenarios).
- Determining which extra parts of the uncertainty space I should explore, and running those models.
- Running extra sensitivities to test the assumptions I have made.
- Considering how I can make my results and write up as relevant as possible for policy makers. This might include analysing the spatial distribution of investment across different model runs.