

Modelling Green Energy Conversion Networks for Generating Hydrogen Electric Vehicle Fuel

Lucas Ng

University of Cambridge

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What are we modelling?



The goal is to turn solar energy into hydrogen fuel to be used in HEVs. Here is a simple linear system for this:

$$\underbrace{ \begin{array}{c} \mathsf{Sun} & \longrightarrow \\ \bullet & \mathsf{PV} \ \mathsf{cells} \end{array} }_{\mathsf{PV} \ \mathsf{cells}} \underbrace{ \begin{array}{c} \mathsf{Battery} \\ \bullet \\ \mathsf{Electrolyser}, \ \mathsf{Compressor} \end{array} }_{\mathsf{Electrolyser}, \ \mathsf{Compressor}} \underbrace{ \begin{array}{c} H_2 \ \mathsf{fuelling} \ \mathsf{station} \\ \bullet \\ \mathsf{Electrolyser}, \end{array} }_{\mathsf{Electrolyser}, \ \mathsf{Compressor}}$$

Observe:

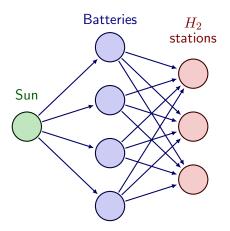
- ▶ The Sun, battery and H_2 fuelling station are energy stores.
- The PV cells and electrolyser are energy converters.

We can abstract this into a graph with:

- Vertices representing energy stores.
- **Edges** representing energy converters.

A more complex example





If this sort of generalised, extensible and extendable approach is consistently taken, it is more useful for future investigation.



Theory



Begin with some definitions:

- lacksquare $\mathcal V$ is the set of vertices mapped to energy stores
- $ightharpoonup \mathcal{E}$ is the set of edges mapped to energy converters
- $\blacktriangleright \ G \triangleq (\mathcal{V}, \mathcal{E}) \ni \mathcal{E} \subseteq \left\{ (x, y) : (x, y) \in \mathcal{V}^2 \text{ and } x \neq y \right\}$
- ightharpoonup N is the cardinality of \mathcal{V} .
- $\underline{\underline{A_w}} \ni \forall v_i \in \mathcal{V}, \nexists j: \left[\sum_{k=1}^N \left(\underline{\underline{A_w}} + \underline{\underline{A_w}}^\top \right)^k \right]_{ij} = 0 \text{ is } G \text{'s weighted adjacency matrix.}$

Hence the graph G is defined to be simple, directed and weakly connected. Normalised edge weights $\in [0,1]$ are used to proportion power transfer ratios.

Non-simple networks can be modelled by edge subdivisions or adjusting edge weights.

Ideal behaviour



Consider a single vertex with energy value u_i .

$$\xrightarrow[\text{Net power in}]{u_i} \xrightarrow[\text{Net power out}]{}$$

Ignoring all constraints causes immediate energy propagation to and from all neighbours.

During time-step Δt :

$$\Delta u_i = -\sum_{j=1}^N \underbrace{\underline{A_w}}_{ij} u_i + \underbrace{\sum_{j=1}^N \underline{\underline{A_w}}_{ji} u_j}_{\text{energy in}}$$

 $\forall \underline{\underline{A_w}}, \forall \underline{u}: \sum_{i=1}^N \Delta u_i = 0$... this operator conserves energy.



Non-ideal behaviour



We have the following non-idealities:

- ▶ Vertex maximum capacity: $u_{i_{max}} \ni 0 \le u_i \le u_{i_{max}}$.
- ▶ Edge maximum power transfer: $\underline{\underline{P}}_{ij}$ $\ni \underline{\underline{Aw}}_{ij} u_i \leq \underline{\underline{P}}_{ij} \Delta t$ where $\underline{\underline{P}}_{ij}$ is the maximum power transfer from i to j.
- ▶ Vertex self-discharge: loss of energy stored over time.
- **Edge process inefficiency**: losses during power conversion.

Ignore the last two for now. We can then apply the remaining constraints to the previous equation:

$$\Delta u_{i} = \min \begin{pmatrix} -\sum_{j=1}^{N} \min(\underline{\underline{A}_{w}}_{ij} u_{i}, \underline{\underline{P}}_{ij} \Delta t) \\ u_{i_{\max}} - u_{i}, & \\ +\sum_{j=1}^{N} \min(\underline{\underline{A}_{w}}_{ji} u_{j}, \underline{\underline{P}}_{ji} \Delta t) \end{pmatrix}$$

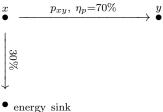
What about power losses?



Consider an arbitrary energy conversion p_{xy} with efficiency η_p .

$$\begin{array}{ccc}
 & & p_{xy}, & \eta_p = 1 & y \\
 & & & & & \bullet
\end{array}$$

If p is not, in fact, ideal, then we can model this by partitioning some power off into an energy wastage sink. Let's suppose it is 70% efficient:



To handle self-discharge losses, increase the weight of the edges connecting vertices to the sink.

Demo: a simple linear system



Studying the simple linear system from earlier to demonstrate the model:

$$\underbrace{ \begin{array}{c} \mathsf{Sun} \\ \bullet \end{array} }_{\mathsf{PV}} \underbrace{ \begin{array}{c} \mathsf{Battery} \\ \bullet \end{array} }_{\mathsf{Electrolyser, Compressor} } \underbrace{ \begin{array}{c} H_2 \text{ fuelling station} \\ \bullet \end{array} }_{\mathsf{Electrolyser, Compressor} }$$

Reasonable assumptions about component behaviour and economics and solar power input over the course of a representative year were used.

Geography-dependent data was sampled for Cyprus.

Results: minimum budget to support HEVs



L-BFGS-B optimisation was used to minimise the total budget required to sustain the system:

# HEVs	Min. budget (€)	Solution η	PV capacity (kW)
1	70.8k	0.55	4.6
10	715k	0.55	46
100	6800k	0.55	460

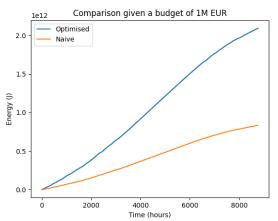
It was not possible to simulate 1000 HEVs due to constraints from the PV data API.

Results: optimising given budget



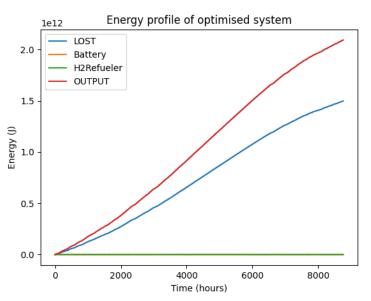
For $\in 1M$, use **L-BFGS-B optimisation** to find the optimal budget allocation that maximises the number of HEVs supported:

PV (€)	Battery (€)	Electrolyser (€)	H_2 station (\in)
645k	244k	107k	3.90k



Results: optimising given budget (cont.)





Future potential



- More accurate modelling of component behaviour, e.g. using characterisations dependent on more parameters.
- Expand components into sub-networks to give a more detailed analysis.
- Investigate larger networks, e.g. a potential national PV-HEV grid.