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On the role of H_2 storage and conversion for wind power-production in the Netherlands

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Abstract

Mixed integer linear programming (MILP) is the state-of-the-art mathematical framework for optimization of energy systems. The capability of solving rather large problems that include time and space discretization is particularly relevant for planning the transition to a system where non-dispatchable energy sources are key. Here, one of the main challenges is to realistically describe the technologies and the system boundaries: on the one hand the linear modeling, and on the other the number of variables that can be handled by the system call for a trade-off between level of details and computational time. With this work, we investigate how modeling wind turbines, H_2 generation via electrolysis, and storage in salt cavern affect the system description and findings. We do this by implementing methodological developments to an existing MILP tool, and by testing them in an exemplary case study, i.e. decarbonization of the Dutch energy system. It is found that modeling of wind turbines curtailment and of existing turbines are key. The deployment of H_2 generation and storage is driven by the interplay between area availability, system costs, and desired level of autarky.

Keywords: MILP, wind turbines, energy storage, technology modeling, energy transition

1. Introduction

A high penetration of non dispatchable renewable energy sources (NDRES) comes with the necessity for energy storage capacity. While batteries show a very high round-trip efficiency and suitability for intra-day storage, they are not suited for long-term storage, especially seasonal, due to their energy losses over time. (Gabrielli et al. (2018a)) The production of hydrogen via power-to-gas (PtG) is a more promising candidate for such long-term storage. Nevertheless, the large volumes required on a national or even international scale require alternatives to conventional gas tanks. Hydrogen storage in salt caverns is a proven technology (Lord et al. (2014)) that features large point storage capacity, especially in the Netherlands and in Germany. Previous studies focusing on Germany (Welder et al. (2018)) have already shown the potential of the described system. Understanding the trade-offs between offshore vs. onshore wind farms, and planning the replacement of old wind installations is a challenging task that benefits from the adaption of rigorous MILP frameworks. Therefore, this work aims at grasping the aforementioned trade-offs by analyzing a hypothetical Dutch energy system consisting of onshore and offshore wind turbines, and PtG systems with hydrogen storage in salt caverns. Furthermore, the extent of autarky achievable with such a system will be quantified.

2. Methodology

The model discussed in this work builds upon the MILP modeling framework reported by Gabrielli et al. (2018b). Following, we focus on new developments within this framework.

2.1. Wind turbine modeling

Various approaches to model wind turbines showing different levels of detail can be found in literature. For instance, Gebraad et al. (2017) did detailed wind power plant modeling while Weber and Shah (2011) used simplified models in an MILP energy system optimization. In this work, the wind turbine's power curve $P(v)$ (eq. (1)) is used as described by Jerez et al. (2015).

$$P(v) = \begin{cases} 0 & \text{if } v < v_{in} \\ P_r \cdot \frac{v^3 - v_{in}^3}{v_r^3 - v_{in}^3} & \text{if } v_{in} \leq v < v_r \\ P_r & \text{if } v_r \leq v < v_{out} \\ 0 & \text{if } v \geq v_{out} \end{cases} \tag{1}$$

where P is the power output, P_r the rated power output (i.e. the maximum capacity), v the windspeed, and v_{in}, v_r and v_{out} the cut-in, rated and cut-out windspeed respectively.

Implementation into the MILP framework: Using historical wind profiles for the full analyzed time horizon allows to tackle the non linearity arising from the power curve in a pre-processing step. The maximum power output P_{max} for a wind turbine is calculated for every hour of the year and passed on to the optimization as a constant vector. Note that P_{max}, being the uncurtailed output for a given windspeed, is different from P_r. The actual output P_{out} is then calculated as

$$\begin{aligned} & P_{out,i,t} \leq P_{max,i,t} \cdot S_i \\ & \qquad 0 \leq S_i \text{ for all } i \in \{1, I\} \text{ and } t \in \{1, T\} \end{aligned} \tag{2}$$

where the integer decision variable S is the number of turbines, I the number of types of turbines and T the length of the time horizon. The optimization can choose to build new turbines from a discrete set (offshore: 3.5 MW and 6 MW, onshore: 0.9 MW, 2.5 MW and 4.5 MW). The treatment of existing turbines is more complicated owing to the limited amount of information open databases provide.

Treatment of existing turbines: The emphasis on a detailed description of the existing turbines arises from the importance of the decision under which circumstances old turbines should be replaced. While it is easy to model a certain turbine in detail, the vast variety of existing turbines calls for a more generalized approach which is described in this section. A data set consisting of 43 turbines, accounting for about 78 % of Dutch turbines, was used. The only clear correlation was found between the rated power and the total integral of the power curve. Based on this observation and the aforementioned set of turbines, an algorithm to calculate estimates of cut-in, cut-out and rated windspeed for arbitrary turbines was developed. The algorithm takes the rated power and the manufacturer of the wind turbine to be analyzed as an input as well as the 43 turbines data set. Knowing that the maximum hourly windspeeds are usually around 10-20 m/s, the cut-out usually ranging from 20-25 m/s is of minor importance and hence neglected here. If the manufacturer of the turbine to be analyzed matches with one from the dataset, the set is reduced to that manufacturer. If it doesn't, or the manufacturer is unknown, the full set is used. The remaining turbines of the data set are compared for their rated power. Depending on how many matches are found, 3 cases are distinguished.

- *Case 1: 1 match for rated power found* The algorithm uses the match from the dataset to simulate the turbine of interest.
- *Case 2: >1 match for rated power found* A target power curve integral I_t is determined as

  $$I_t = \frac{\sum_{i=1}^{N_m} \int_0^{v_{r,max}} P_i(v_{in}, v_r, v)\mathrm{d}v}{N_m} \tag{3}$$

  where $v_{r,max}$ is the maximum rated windspeed found in the data set and N_m is the total number of rated power matches found. The cut-in and rated windspeed are then calculated solving eq. (4)

  $$\begin{aligned} \min_{v_{in}, v_r} g &= \left| \int_0^{v_{r,max}} P(v_{in}, v_r, v)\mathrm{d}v - I_t \right| \\ \text{s.t. } & v_{in,min} \leq v_{in} \leq v_{in,max} \\ & v_{r,min} \leq v_r \leq v_{r,max} \end{aligned} \tag{4}$$

  The cut-out windspeed is returned as the average of the values in the considered data subset.
- *Case 3: No turbines found* In this particular case, the turbines with the next higher and next lower rated power are chosen. If more than one turbine each is found, their integrals are averaged as seen in eq. (3) to end up with one upper and one lower value. I_t is then obtained by simple interpolation. If P_r of the turbine of interest is higher or lower than all turbines in the considered subset, the whole subset forms the basis for a linear fit that allows to calculate I_t by means of extrapolation. Once I_t is obtained, the remaining procedure is identical to Case 2, i.e. solving eq. (4) for v_{in} and v_r and averaging v_{out}.

Curtailment: While the inequality in eq. (2) already allows for curtailment, this formulation is imprecise from a physical point of view since wind turbines are curtailed in a discrete manner. They are either curtailed, i.e. turned off, or operated following their power curves. To account for this effect, the curtailment C was introduced as an additional integer decision variable, describing how many turbines are turned off. The power output can then be formulated as

$$\begin{aligned} P_{out,i,t} &= P_{max,i,t} \cdot (S_i - C_{i,t}) \\ 0 &\leq C_{i,t} \leq S_i \\ 0 &\leq S_i \\ 0.25^2\pi \cdot \sum_i S_i &\leq A_{max} \end{aligned} \tag{5}$$

Note the strict equality in eq. (5), as compared to eq. (2), is reducing the flexibility of the system. This formulation allows for a physical-based description of curtailment, but it also increases significantly the complexity of the problem as discussed in the results. The total number of turbines is constraint by the maximum available land A_{max}. It is assumed that the distance between two wind turbines has to be at least 500 m, giving each turbine a radius of 0.25 km.

2.2. Power-to-gas

The power-to-gas system consists of a polymer electrolyte membrane (PEM) electrolyzer and fuel cell, operating with water and air, respectively. Their modeling is reported in detail by Gabrielli et al. (2018b).

2.3. Hydrogen storage

Hydrogen is considered to be stored in cylindrical salt caverns as described in Gabrielli et al. (2018c).

3. Case Study

The system under investigation consists of 3 nodes, hereafter called onshore-node (ONN), offshore-node (OFFN), and cavern-node (CN). All data refers to the Netherlands and is hourly resolved. The considered time span is the full year 2017. The technologies and input data profiles for each node are summarized in Table 1. Full connectivity between the nodes is assumed for the electricity network while the hydrogen network needs to be built if required, i.e. investment costs occur. The optimization decides upon selection, sizing, and scheduling of the technologies as well as the flows between the nodes. While there is no export of electricity allowed, electricity can be imported at a price of 0.032 euro/kWh and an emission factor of 0.676 kg_{CO_2}/kWh. A CO_2-tax of 20 euro/t was applied, corresponding to the current ETS prices. The available land for ONN was assumed to be 15 % of the total land (WorldBank (2018),McKenna et al. (2015)). For OFFN, a total available area of 2900 km^2 (Dutch Government (2014)) was assumed. The total levelized costs of the system were used as objective function.

4. Results

The problem was formulated in MATLAB R2018b using YALMIP (Löfberg (2004)) and solved with Gurobi v8.1 on an Intel Xeon E5-1620 3.60 GHz machine with 16 GB RAM.

4.1. Case study

The case study was analyzed with continuous curtailment for computational reasons. Existing wind turbines were not considered because the major objective in this analysis is the interaction between PtG and wind turbines and the effect on achievable autarky. Since imported electricity is the only source of emissions, the maximum achievable autarky was determined by applying a CO_2-tax of 10^6 euro/kWh giving an autarky of 62.5 % (defined as the fraction of the produced electricity over the total demand). Following, the autarky was implemented as a constraint and the sensitivity of the technologies towards this constraint was investigated (see Table 2). It can be observed that in order to achieve the upper limit of autarky, oversizing of production technologies and installation of PtG is necessary. As soon as the constraint on autarky is relaxed, undersizing of production technologies and compensation with import is the preferred combination. Note that this result is also sensitive to the import price, the CO_2-tax, and the emission factor of imported electricity. The difference in size between PEMEC and PEMFC indicates that the amplitudes in overproduction are greater than in overdemand. Nevertheless, it does not necessarily follow that the total production for a year is higher than the demand.

4.2. Computational aspects

The introduction of discrete curtailment increases the computational complexity by drastically increasing the number of integer variables. For the Dutch case study, this resulted in a non-solvable problem due to lack of memory caused by the increased effort in the branch-and-bound algorithm.

5. Conclusions

In this work, the implementation of wind turbines with its various aspects into an MILP framework and in particular the consideration of existing turbines was discussed. A first analysis of the Dutch case study shows how the level of targeted autarky affects the selection of technologies. An upper limit to autarky is given by the available land and PtG is required to approach this limit. From a computational point of view, the description of the wind turbine curtailment strongly affects the problem complexity, physical based

Table 1: Summary of technologies and input profiles for the analyzed nodes. *Abbreviations: WT = wind turbine, PEMEC/FC = polymer electrolyte membrane electrolytic cell / fuel cell*

Node	Existing Technologies	Additional Technologies	Input Profiles
Onshore	various WT	WT, PEMFC, PEMEC	electricity demand, wind
Offshore	various WT	WT	wind
Cavern	-	PEMFC, PEMEC, salt cavern storage	-

Table 2: Sensitivity of technology implementation towards level of autarky. The sizes for electrolyzer (PEMEC) and fuel cell (PEMFC) are in kW capacity, and for the wind-turbines (WT) in built units. The number next to *WT* refers to its maximum capacity in MW

Autarky	PEMEC	PEMFC	WT-0.9	WT-2.5	WT-4.5	WT-3.5	WT-6.0
0.625	42586	423.8	0	26944	4792	1077	24
0.475	0	0	0	15223	0	0	0
0.325	0	0	0	7520	0	0	0
0.175	0	0	0	3687	0	0	0
0.025	0	0	0	531	0	0	0
0	0	0	0	0	0	0	0

modeling of wind turbines might result in too many integer variables.

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