# Alleviate energy system model distortions through variable costs

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## Abstract

Unintended storage cycling is a modelling artifact that may unknowingly appear in many energy system models. It is observable through simultaneous charging and discharging of the same storage unit, when instead of curtailing renewable surplus electricity, unintended storage cycling creates energy losses that distorts optimal dispatch decisions across space and time. Originally unintended storage cycling was attributed to models that use renewable energy targets constraining the optimization problem, however, it also arises in energy models that deviate from such formulations. In this paper, we explore how correctly setting variable costs of relevant system components can eradicate unintended storage cycling for these models. We find through 124 simulations that determining appropriate levels of variable costs depends on the solver accuracy used for the optimization. If set too loose, the solver prevents the removal of unintended storage cycling. We further find that reliable data for variable costs in energy modelling needs to be improved and provide a list of recommended model inputs as well as a minimum variable cost threshold that can significantly reduce the magnitude and likeliness of unintended storage cycling. Finally, our results also suggest that variable cost additives may remove other known unintended energy cycling effects, such as unintended line cycling or sector cycling.

*Keywords:* Unintended storage cycling, Energy storage, Line cycling, Sector cycling, Energy system modelling, Optimization

## 1. Introduction

Energy system models are mathematical models used to investigate possible pathways for decarbonising our energy systems, in many cases minimising total system costs [1]. They provide insights on optimal dispatch and investment patterns in the short- and long-term, which not only guide energy technology design decisions [2], but also support the decision making of governments, grid operators, energy system planners, manufacturers, and researchers. However, if not carefully used, such models can mislead developments.

One model artifact distorting optimal model results is unintended storage cycling (USC) [3]. The effect can be observed by simultaneous charging and discharging of the same storage capacity, which removes surplus electricity of variable renewable energy sources (VRE) from the system in form of unintended storage losses instead of curtailing it. USC may also manifest across space and time (see Figure 1). For instance, USC across space may occur in multi-regional model settings through simultaneous charging in one region and discharging at another region for the only purpose to dissipate renewable surplus energy instead of curtailing it, notably in the absence of transmission costs. Similar, USC across time represents unnecessary charging and discharging cycles across multiple periods [3]. That USC is not bound to the same spatial and temporal cycling moments aligns also with the non-guaranteed operational uniqueness in scenarios with multiple storage assets [4]. Here, a convex linearly formulated problem has an unique objective value with multiple non-unique operational solutions. This means, multiple ways exist to distribute the storage and generation operation temporally and spatially, in the absence of spatial limitations (i.e., free available idle transmission capacity) or temporal limitations (i.e., free available idle energy store capacity) for connected time periods. In summary, USC over space and time may arise in a non-unique pattern as long as it does not break any constraint or lead to higher costs.

USC appears under various model settings and may cause different significant impacts. In model settings with binding renewable targets, USC flaws optimal dispatch and investment decisions of generators and storage [3]. In models where renewables are not constrained, which are in the focus of this study, USC does not necessarily impact the investment decision outputs of energy system models but can negatively distort its operational outputs. For example, as qualitatively shown in Figure 2, energy storage or renewable generators might have significantly more full load hours (FLH) in a scenario with, compared to one without USC. The notion of FLH describes how many hours a technology would operate under full load during one year or 8760 hours.

The mathematical reason for USC in cost minimising models without binding renewable targets is that the cost of unintended storage losses is equal to or smaller than VRE curtailment cost. For instance, it is practically indifferent to the mathematical model to curtail renewables (no USC) or dissipate energy by cyclic storage operation (USC) at times with 100% solar and wind power penetrations, when cost of storage use, generation and curtailment are zero. In this case, renewable curtailment

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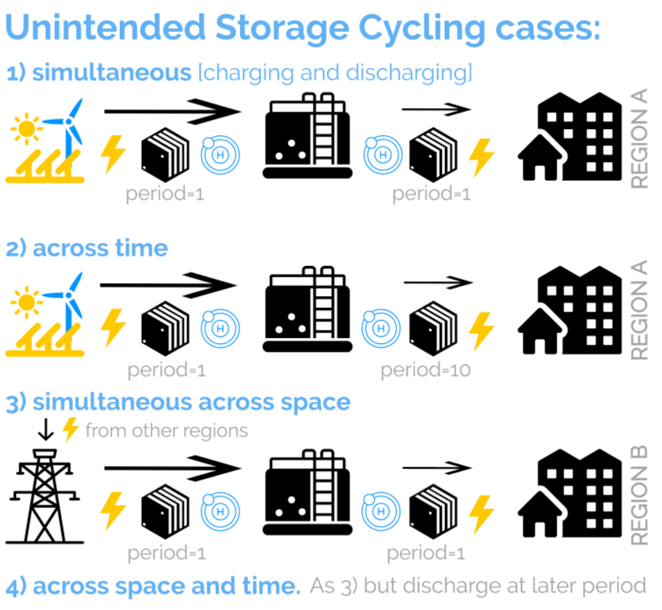


Figure 1: Unintended storage cycling cases in a hydrogen storage example. The left stack represents the electrolyser, the right one, the fuel cell which converts electricity to hydrogen and vice versa, respectively. The arrow size above the storage components reduces to indicate an efficiency drop. Under renewable energy surplus (variable cost = 0), excess energy is removed from the system by storage cycling instead of renewable curtailment. Thereby, USC may occur over space and time if no constraint prohibits this artifact.

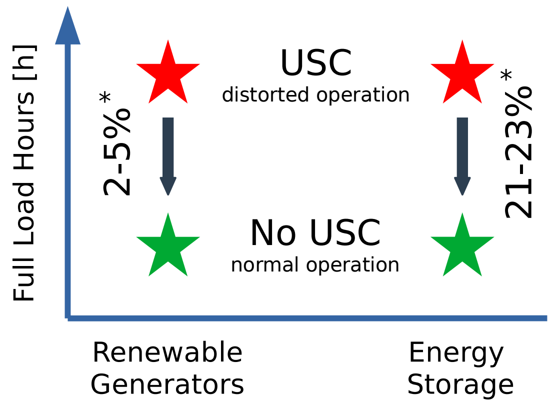


Figure 2: Exemplary impact of scenarios with and without USC on storage and renewable generation. The USC effect increases the operation of close to zero variable cost assets. Results from a numerical analysis conducted in this study, marked with an asterisk (*), show FLH differences of up to 23% for energy storage and 5% for renewable assets in a 100% renewable energy system scenario.

and cyclic storage dissipation are leading to the same total system cost which gives the optimization no reason to prohibit USC - unless the model is not otherwise constraint.

USC is an unrealistic effect that should be removed. Battery storage, such Li-ion storage are one example where USC is technically infeasible. A reason is that the inverter component can either charge or discharge but not both simultaneously. Since, battery storage are optimised in most energy system models [2, 5–7], introducing operational distortion through USC therefore urges it removal.

USC is not the only such misleading effect. There is a group of similar effects classified under the term unintended energy losses, which arise in a cyclic manner [3]. Unintended, because it distorts optimization results. Cyclic, as it occurs wherever efficiency losses are present between energy components that can cycle by charge and discharge, send and receive, or convert and re-convert operations. Other examples beyond USC are unintended line cycling, where unintended energy losses occur by simultaneous sending and receiving of power in lines [3, 8]. Further, unintended energy losses in sector coupling options [3], where for instance electricity is converted to heat by boilers and re-electrified at the same time with organic Rankine Cycle plants.

Previous research dealt with unintended energy losses by ignoring them as they are irrelevant when occurring rarely under zero to negative nodal prices [9], or penalising general active power losses, which can be too simplified and distort the model outputs by falsely allocating the costs [10]. Other studies created a high number of linear constraints, reformulated the problem to a quadratic or mixed-integer problem which are harder to solve [11]. Especially, the mixed-integer solution which prohibits with binaries simultaneous charging and discharging cannot guarantee the full USC removal, because USC is not limited to same-period cycling, but may also manifest across space and time [3].

This paper investigates how to remove USC in linearly formulated energy models without binding renewable energy targets. We show that this can be done by a deliberate setting of variable costs of affected system components. More specifically, we

- formalise mathematically how USC occurs,
- explore the impact of USC and its removal on operational and investment decisions as well as total system cost in a decarbonised German energy system model
- demonstrate how variable costs, their magnitude, allocation can remove USC,
- investigate the role of the solver accuracy in an appropriate setting of variable costs,
- review variable cost inputs of relevant system components to remove USC.

While this study focuses only on energy system model results regarding energy storage, its results may apply to all other unintended energy losses in energy models without a renewable energy constraint.

## 2. Methods

### 2.1. Model formulation

The occurrence of USC depends on the model formulation [3]. This section introduces a general formulation of investment and dispatch optimization problems for energy system models that abstain from binding renewable energy target constraints. The objective of such models is to minimise the total system costs, comprised of annualised capital and operational expenditures. Capital expenditures include capacity-related, long-term investment costs $c$ at location $i$ for generator $G_{i,r}$ of technology $r$, storage energy capacity $H^{store}_{i,s}$, charging capacity $H^{+}_{i,s}$ and discharging capacity $H^{-}_{i,s}$ of technology $s$ and transmission line $F_l$. Operational expenditures include energy-related variable cost $o$ for generation $g_{i,r,t}$ and storage charging $h^{+}_{i,r,t}$ and discharging $h^{-}_{i,r,t}$, as well as energy-level related storage cost $e_{i,s,t}$. Thereby, the operation depends on the time steps $t$ that are weighted by duration $w_t$ that sums up to one year $\sum_{t=1}^{T} w_t = 365 days * 24h = 8760h$.

$$\begin{aligned}
&\min_{G,H,F,g,h,e} \quad \text{(Total System Cost)} = \\
&\min_{G,H,F,g,h,e} \quad \Bigg[ \sum_{i,r} (c_{i,r} \cdot G_{i,r}) + \sum_{l} (c_l \cdot F_l) \\
&\quad + \sum_{i,s} (c^{store}_{i,s} \cdot H^{store}_{i,s} + c^{-}_{i,s} \cdot H^{-}_{i,s} + c^{+}_{i,s} \cdot H^{+}_{i,s}) \\
&\quad + \sum_{i,r,t} (o_{i,r} \cdot g_{i,r,t} \cdot w_t) + \sum_{i,s,t} ((o^{+}_{i,s} \cdot h^{+}_{i,s,t} + o^{-}_{i,s} \cdot h^{-}_{i,s,t}) \cdot w_t) \\
&\quad + \sum_{i,s,t} (o^{store}_{i,s} \cdot e_{i,s,t} \cdot w_t) \Bigg]
\end{aligned} \tag{1}$$

The objective function can be subject to multiple linear constraints, an example is laid out in more detail in [12, 13], leading to a convex linear program. These include:

- nodal power balance constraints guaranteeing that supply equals demand at all times,
- linearised power flow constraints modelling the physicality of power transmission (Kirchhoff's Voltage and Current Law),
- hourly solar and wind resource availability constraints limiting the renewable generation potential based on reanalysis weather data,
- land-use constraints, restricting the renewable capacity expansion based on environmental protection areas, land use coverage, and distance criteria, and finally,
- emission constraints introducing a limit of $CO_2$ equivalent greenhouse gas emissions.

Storage charging $h^{+}_{i,s,t}$ and discharging $h^{-}_{i,s,t}$ are both positive variables and limited by the installed capacity $H^{+}_{i,s,t}$ and $H^{-}_{i,s,t}$.

$$0 \leq h^{+}_{i,s,t} \leq H^{+}_{i,s} \quad \forall i, s, t \tag{2}$$

$$0 \leq h^{-}_{i,s,t} \leq H^{-}_{i,s} \quad \forall i, s, t \tag{3}$$

This formulation keeps the feasible solution space convex.

The storage energy level $e_{i,s,t}$ is the result of a balance between energy inflow, outflow and self-consumption. Additional to directed charging and discharging with its respective efficiencies $\eta_{i,s,+}$ and $\eta_{i,s,-}$, natural inflow $h^{inflow}_{i,s,t}$, spillage $h^{spillage}_{i,s,t}$ as well as standing storage losses that reduces the storage energy content of the previous time step by a factor of $\eta_{i,s,+}$ are considered.

$$\begin{aligned}
e_{i,s,t} &= \eta_{i,s,+} \cdot e_{i,s,t-1} + \eta_{i,s,+} \cdot w_t \cdot h^{+}_{i,s,t} - \eta^{-1}_{i,s,-} \cdot w_t \cdot h^{-}_{i,s,t} \\
&\quad + w_t \cdot h^{inflow}_{i,s,t} - w_t \cdot h^{spillage}_{i,s,t} \quad \forall i, s, t
\end{aligned} \tag{4}$$

The amount of energy that can be stored is limited by the energy capacity of the installed store unit $H^{store}_{i,s}$ [MWh], which allows independent storage component scaling.

$$0 \leq e_{i,s,t} \leq H^{store}_{i,s} \quad \forall i, s, t \tag{5}$$

To fix the storage technology design, a technology-specific energy to discharging power ratio $\overline{T}_s$ can be multiplied with the capacity of the discharging unit $H^{-}_{i,s}$

$$0 \leq e_{i,s,t} \leq \overline{T}_s \cdot H^{-}_{i,s} \quad \forall i, s, t \tag{6}$$

to define the upper energy limit per installed storage.

Finally, energy storage units are assumed to be cyclic, i.e., the state of charge at the first and last period of the optimization period $T$ (i.e. 1 year) must be equal:

$$e_{i,s,0} = e_{i,s,T} \quad \forall i, s \tag{7}$$

This cyclic definition is not mandatory but helps with the comparability of model results. It further avoids the free use of storage energy endowment, meaning that the model could prefer to start with a higher and end with a lower storage level to save costs.

### 2.2. Detecting unintended storage cycling occurrence

USC can be identified by analysing storage charging and discharging patterns. A straightforward approach is to count the occurrence of simultaneous charging and discharging over the optimization horizon which we use in later parts of the study. Here, USC may occur under three cases in energy systems with energy storage [3]: During effective charging, effective discharging, or in an idle energy state with effective net-zero charging.

The storage charging power $h^{+}_{i,s,t}$ describes the power provision from the grid to the charging component. If reduced by the charging efficiency $\eta_{i,s,+}$, it results in store charging power $h^{+}_{i,s,t,store}$ that increases the storage energy level over time.

$$h^{+}_{i,s,t,store} = \eta_{i,s,+} \cdot h^{+}_{i,s,t} \tag{8}$$

Likewise, store discharging power $h^{-}_{i,s,t,store}$ describes the power provision from the storage that reduces the storage energy level over time. If reduced by the discharging efficiency $\eta_{i,s,-}$, it results in the storage discharging power $h^{-}_{i,s,t}$ that provides power to the grid.

$$h^{-}_{i,s,t,store} = \frac{h^{-}_{i,s,t}}{\eta_{i,s,-}} \tag{9}$$

The first case USC occurs under effective charging $USC^{+}_{i,s,t}$, which increases the storage energy level over time:

$$\begin{aligned} if \quad & h^{+}_{i,s,t,store} > h^{-}_{i,s,t,store} \quad \text{and} \quad h^{-}_{i,s,t,store} > 0: \\ & \mathrm{USC}^{+}_{i,s,t} = \text{true} \end{aligned} \tag{10}$$

The second case occurs under effective discharging $USC^{-}_{i,s,t}$, which decreases the storage energy level over time:

$$\begin{aligned} if \quad & h^{+}_{i,s,t,store} < h^{-}_{i,s,t,store} \quad \text{and} \quad h^{+}_{i,s,t,store} > 0: \\ & \mathrm{USC}^{-}_{i,s,t} = \text{true} \end{aligned} \tag{11}$$

The third case appears under non-zero equal charging and discharging $USC^{=}_{i,s,t}$, or idle energy state, which keeps the storage energy level over time constant (neglecting standing losses):

$$\begin{aligned} if \quad & h^{+}_{i,s,t,store} = h^{-}_{i,s,t,store} \quad \text{and} \quad h^{+}_{i,s,t,store} > 0: \\ & \mathrm{USC}^{=}_{i,s,t} = \text{true} \end{aligned} \tag{12}$$

### 2.3. Removing unintended storage cycling by variable cost additives

We define variable cost additives as not necessarily true observed variable costs, but more generally as assumed additional costs components.

Suppose an optimization found a least cost total system architecture. Then the system operation may adapt any value as long as it does not lead to more cost (left side of Equation (13) and (14)) and does not break constraints such as demand is equal supply (described in 2.1).

Further suppose, the energy system contains a renewable energy surplus at a time step, and variable operational cost $o_{i,s/r}$ of storage and renewables are assumed as zero, then:

$$0 \quad = \underbrace{o_{i,r}}_{0} \cdot g^{*}_{i,r,t} + \underbrace{o^{+}_{i,s}}_{0} \cdot h^{*,+}_{i,s,t} + \underbrace{o^{-}_{i,s}}_{0} \cdot h^{*,-}_{i,s,t} + \underbrace{o^{store}_{i,s}}_{0} \cdot \triangle e^{*}_{i,s,t} \tag{13}$$

These zero costs may lead to a situation where surplus generation is fed into the grid rather than curtailed. However, to guarantee the energy balance the extra surplus generation needs to be dissipated by USC (indicated by $^{*}$), which leads to higher storage usage.

In contrast, in case costs exist for either generation or storage operation,

$$0 \quad = o_{i,r} \cdot \underbrace{g_{i,r,t}}_{0} + o^{+}_{i,s} \cdot \underbrace{h^{+}_{i,s,t}}_{0} + o^{-}_{i,s} \cdot \underbrace{h^{-}_{i,s,t}}_{0} + o^{store}_{i,s} \cdot \underbrace{\triangle e_{i,s,t}}_{0} \tag{14}$$

every additional operation of variable renewable generators or storage is prevented in the first place, avoiding USC.

Equations (13) and (14) illustrate that a system with USC (indicated by $^{*}$) has components with higher operating hours than one without,

$$\sum_{t=1}^{T} g^{*}_{i,r,t} \geq \sum_{t=1}^{T} g_{i,r,t} \tag{15}$$

$$\sum_{t=1}^{T} h^{*,+/-}_{i,s,t} \geq \sum_{t=1}^{T} h^{+/-}_{i,s,t} \tag{16}$$

$$\sum_{t=1}^{T} e^{*}_{i,s,t} \geq \sum_{t=1}^{T} e_{i,s,t} \tag{17}$$

caused by energy dissipation through excessive storage use rather than curtailing renewable surplus.

In summary, to remove USC, a situation with USC must become more expensive than one without because, fundamentally, the objective function aims to minimise cost. One approach is to add variable cost $o_{i,r} > 0$ to the generation dispatch. Another one is to add variable costs $o_{i,s} > 0$ to any or all energy storage components such as charger, store or discharger. Both such variable cost additives penalise any extra operation of generators or storage units caused by USC energy dissipation even across space and time. Nevertheless, since variable costs not only penalise USC but all operation of these units, they need to be carefully chosen.

### 2.4. Numerical implementation and data

We use PyPSA-Eur [13] as a numerical implementation for the model defined in Section 2.1 to explore the occurrence and amplitude of USC. PyPSA-Eur is a European power system model, representative to energy models that abstain from binding renewable energy targets. We apply the model to a stylised setting parameterised to the German power sector for a 100% greenhouse-gas emission reduction scenario. We limit the available set of technologies to solar PV, onshore wind, offshore wind, as well as hydrogen (H2) storage system consisting of a electrolyzer, a tank, and a fuel cell. We set the spatial resolution to 16 nodes within Germany. Offshore wind power plants may be connected via alternative current (AC), or, in the case of sites far off shore, more costly direct current (DC) transmission lines. The model has perfect foresight, and optimises with an hourly temporal resolution. Weather and load data stem from 2013. Hourly load data originates from the ENTSO-E Transparency platform and are distributed across the regions depending on NUTS3 based GDP data (see more in [13]). All renewables and energy storage technologies are greenfield optimised, i.e., without considering the existing capital stock. State of charge of energy storage capacities is constrained to start and end with 100%. The self-consumption of the H2 storage tank is assumed to be zero. The transmission network is based on the current network topology, considering also planned lines until 2030 from the ENTSO-E Ten Year Network Development Plan (TYNDP) 2018 [18]. Grid expansion is endogenous but limited to additional 25% new built lines for modelled target year to represent political hurdles of transmission expansion [12]. Table 1 lists relevant techno-economic assumptions. This stylized setting allows for demonstrating USC in the context of energy models without binding renewable energy targets, and how it can be removed by a deliberate setting of variable costs.

Table 1. Model input assumptions.

| Technology [a] | Investment [€/kW] | Fixed O&M [€/kW/a] | variable cost [b] [€/MWh] | Lifetime [a] | Efficiency [-] | Source |
|---|---|---|---|---|---|---|
| onshore wind | 1040 | 25 | variable | 30 | 1 | DEA [14] |
| offshore wind (AC connected) | 1890 | 44 | variable | 30 | 1 | DEA [14] |
| offshore (DC connected) | 2040 | 47 | variable | 30 | 1 | DEA [14] |
| photovoltaic (PV) | 600 | 25 | variable | 25 | 1 | Schröder et al. [15] |
| hydrogen electrolyser | 350 | 14 | variable | 25 | 0.8 | Budischak et al. [16] |
| hydrogen storage tank | 8.44 €/MWh | - | variable | 20 | 1 | Budischak et al. [16] |
| hydrogen fuel cell | 339 | 10 | variable | 20 | 0.58 | Budischak et al. [16] |
| transmission (submarine) | 2000 €/MWkm | 2%/a | 0 | 40 | 1 | Hagspiel et al. [17] |
| transmission (overhead) | 400 €/MWkm | 2%/a | 0 | 40 | 1 | Hagspiel et al. [17] |

[a] All technologies include a discount rate of 7%.
[b] 'Variable' means set according to scenarios.
[c] Unconstrained energy storage sizing and not fixed to a specific energy to power ratio.

### 2.5. *Experimental setup*

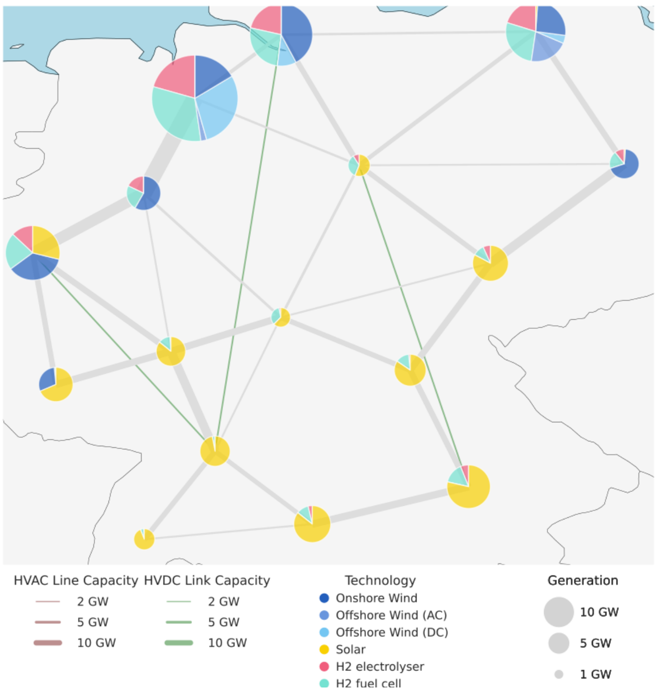


Figure 3: Optimised generation and storage capacities in Germany for a 100% GHG emission reduction scenario.

To investigate the suggested method for removing USC, in the base case scenario we set the variable cost (EUR/MWh) of the renewable generators, H2 electrolysers, H2 tanks, and H2 fuel cells to zero. We then define further scenarios varying *ceteris paribus* the variable cost of one of these system components in the range $e \in \{0, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 10^{0}, 10^{1}, 10^{2}, 10^{3}\}$. Which means in each scenario, the variable cost of one system component changes according to range $e$, while the others are kept constant at zero. Note that in the respective scenarios variable costs of all renewable generators are varied at once.

The double-precision arithmetic limits the amount of numbers a computer can recognise. While optimization solvers are also influenced by the double-precision arithmetic they additionally include tolerances to faster solve problems in cost of accuracy. We vary the precision of two Gurobi solver parameters simultaneously yielding three scenarios: low, medium, and high accuracy. The first modified Gurobi parameter that impacts the precision is the *FeasibilityTol* or primal feasibility tolerance, which requires all constraints to satisfy a specific tolerance to be feasible [19]. For instance, constraints such as $(a * x) <= b$ require to hold $(a * x) - b <= FeasibilityTol$ expanding the solution space. We vary this value by $e \in \{10^{-5}, 10^{-6}, 10^{-7}\}$ from low to high accuracy. Simultaneously, we vary the Gurobi parameter *BarConvTol*, which describes the barrier solver (also known as interior point method (IPM)) termination tolerance as relative difference between the primal and dual objective values [19]. Given one solution space for a optimization problem this relative difference is also known as duality gap [20] which IPM's reduces iteratively towards zero before the termination tolerance is reached. We vary this value by $e \in \{10^{-4}, 10^{-5}, 10^{-6}\}$, again, from low to high accuracy.

The computations to generate all results ($10 * 4 * 3 = 120$ scenarios) required 25.5 h for 1 CPU core with 8GB memory.

## 3. Results and discussion

In the following subsections, we investigate the impact of USC and its removal on model outcomes such as optimal dispatch, installed capacity, and total system cost.

### 3.1. *Effects on operational optimization*

Figure 4 illustrates the number of hours with USC in the system (scatter plots, right ordinate). It further shows FLH of the H2 fuel cell for varying variable costs of the renewable generators or H2 storage components (lines, left ordinate). Adding variable cost to any class of storage components or all renewables can successfully remove USC beyond a certain threshold which depends on the solver accuracy. The observed occurrence of USC, spatially averaged over all modelled nodes with variable cost below $10^{-3}$ is roughly 5200 across all levels of solver accuracy.

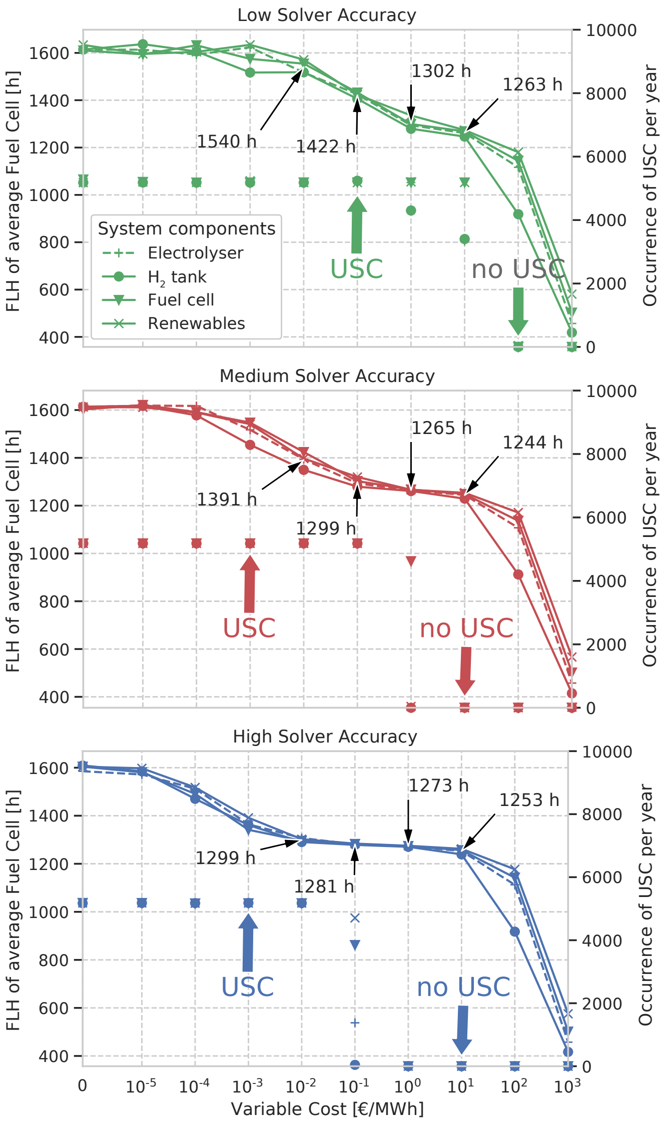


Figure 4: FLH of the H2 fuel cell (lines, left ordinate) and occurences of USC (scatter plots, right ordinate) for three levels of solver accuracy (low, medium, high from top to bottom) across different levels of variable cost additives for renewable generators or H2 storage components (abscissa). FLH are averaged across all nodes in Germany. Per scenario, the variable cost additives are added to only one component, while no variable costs accrue for all others.

Figure 4 reveals that the level of the variable cost additives must be carefully set. If the variable cost additives are set too high, the optimization may be affected. Because its increased operational cost not only remove USC, but may penalise the operation. For instance, in the medium solver accuracy scenario, no USC arises for variable costs ranging from 10 to 1000 €/MWh of any component, while the H2 fuel cell operation reduces from roughly 1244 to 500 FLH. Such high variable cost levels are unrealistic for VRE or other components (see Table 3.4), but clearly illustrate the impact of choosing unreasonably high values.

In contrast, when setting variable cost additives too low, then the applied solver tolerance does not guarantee the USC removal, distorting the optmization results. In our stylized setting at medium solver accuracy, which refers to the PyPSA-Eur default values [21], USC is fully removed in any considered scenario with an observed variable cost threshold at 10 €/MWh or 1 ct/kWh. However, variable cost of 1 €/MWh might be sufficient to avoid USC as the FLH difference of roughly 21h (1265h - 1244h) suggest that the volume of distortions is not significant. Further, increasing or decreasing the solver accuracy changes the minimal required variable costs to remove USC by one order of magnitude for all component classes.

These above observed impacts of USC on the operation are an extreme. The operational distortions are amplified in this study with 100% GHG reduction scenarios and the exclusion of dispatchable renewable and conventional generators, such as biomass, nuclear, or green gas. For instance, including such dispatchable generators may decrease the appearance of USC in many energy models since they introduce variable costs that prevents its appearance (see Section 2.3). As result, models with less ambitious GHG reduction scenarios and more operation of non-zero variable cost generators may lower USC distortion and therefore its relevance.

### 3.2. *Effects on investment optimization*

The amount of desirable energy assets, such as wind power or solar power plants, for future scenarios is not impacted by USC. In our stylised setting, the optimised assets in the energy system are nearly the same with or without USC unless the variable cost additives are not too high such as observed above 10 €/MWh. Therefore the results suggest, in models without renewable energy constraint, USC has only a negligible impact on investment optimization.

Figure 5 illustrates the optimised generation and storage capacity of all modelled scenarios. Results of the previous section suggest that USC may arise below 1 €/MWh for the chosen solver configurations under the given scenarios. The nearly constant optimised generation and storage capacity between scenarios with 0 and 1.0 €/MWh, implies that the impact of USC on the optimised capacity is negligible in this study.

However, if the variable cost of any component are increased above or equal to 10 €/MWh to deal with USC, optimal installations of storage components reduce, while wind capacity increases. Because storing energy becomes more expensive by increasing variable variable costs, the model tries to overbuild generation capacity to reduce situations that require energy storage operation. This effect is obvious when the operation of storage components are penalised with variable costs. However, less obvious when adding variable cost to renewables generators.

Even though variable costs are added only to generator operations, the use of storage becomes more expensive. The reason is the efficiency drop in storage technologies always multiplies generation cost. For instance, if one charges a storage with electricity for 100 €/MWh at 50% and discharges at 50% (roundtrip 25%), the total cost for cycling becomes now 400 €/MWh (four times more energy must be input to generate one output) making the actual cost of production higher. This multiplication effect of generation costs in energy storage components would be less of an issue if generation were cheap in the first place. For instance, consider generation costs of 0 €/MWh for the same efficiency as before. The effective operation costs of charging and discharging are equal to zero - causing USC.

### 3.3. *Effects on total system costs*

The total system costs consist of operational and investment cost and is a key parameter to assess the wider energy system. Figure 6 shows the total system cost results for all simulation stacked by system components. It reveals that scenarios with USC and applied USC removal strategies have only negligible impact on the total system costs, unless the variable costs are set too high (above or equal to 10 €/MWh). Depending on which technology the variable costs are added, a significant cost increase can be detected due to the extra operational cost that needs to be covered. Again, the assumed values, for instance, of 100 €/MWh for the dispatch of all included renewables, might not be realistic but illustrate the impact of mistakenly choosing the wrong values.

### 3.4. *Setting variable costs right*

Our results suggest that variable costs should be carefully set for all assets to guarantee the removal of USC and to avoid any distortion of optimal investment and dispatch decisions. If variable operational cost are assigned to technologies, these should be ideally used instead of being ignored. If technologies are given no or too small values so that solvers can't recognise them, these values should be replaced by a minimum value depending on the solver accuracy and used solver. For PyPSA-Eur this minimum value can be 1 €/MWh at the used default Gurobi solver settings of ($BarConvTol = 1e^{-5}$, $FeasibilityTol = 1e^{-6}$), which removes in our performed optimization results most USC effects. This suggestion might even generalise to other similar PyPSA-Eur optimizations with more technologies and higher spatial-temporal resolution, since what matters is that the solver detects such variable costs.

Replacing the zero variable cost by a minimum cost threshold is the key to avoiding USC. However, this threshold does not need to be placed on all components. In case of energy storage, setting minimal variable costs to prevent USC is only necessary for either one storage component (charger, store or discharger) or all generation types at all locations (see Equations 13 and 14). So while adding variable costs to one of this components to remove USC is enough, we suggest correctly setting variable costs for all assets may reduce the possibility of mistakes and unintended distortions.

Moreover, assuming zero costs for energy dispatch could be reconsidered. The here coined concept of 'variable cost for lifetime reductions' may justify little cost assumptions for non-zero dispatch generators or storage components. A thought experiment might convince that this can be straightforward. Let's assume that a wind turbine operates 100% and another one only 50% of all hours of the year. Further, both turbines are

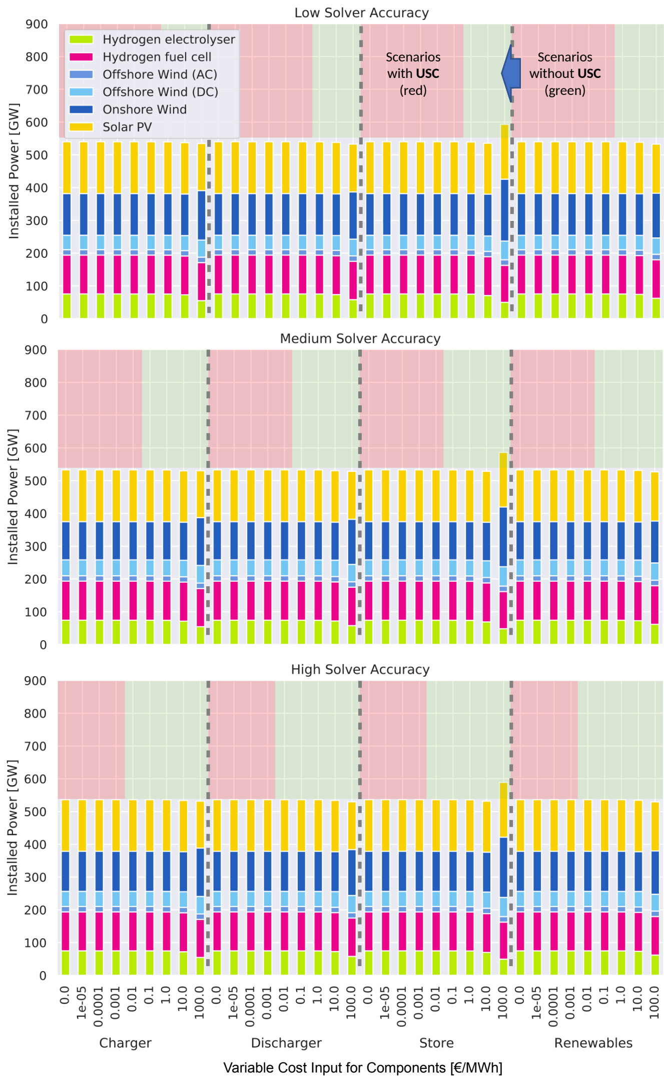


Figure 5: Installed capacity of all generation and storage assets for different variable cost additive scenarios. Scenarios in red are impacted by USC while the green ones are not. USC causes negligible changes in the installed or optimised capacity; if not variable cost additives are too high. Variable cost additives beyond 10 €/MWh penalise especially storage operation, thus reducing its value of being installed. Note that 100 €/MWh or 10 ct/kWh represents a demonstrative, non-realistic value for all included technologies which could be interpreted as falsely set variable costs. We omit illustrating results from the scenarios using variable costs additives of 1000 €/MWh to keep Figure 5 and **??** consistent and readable.

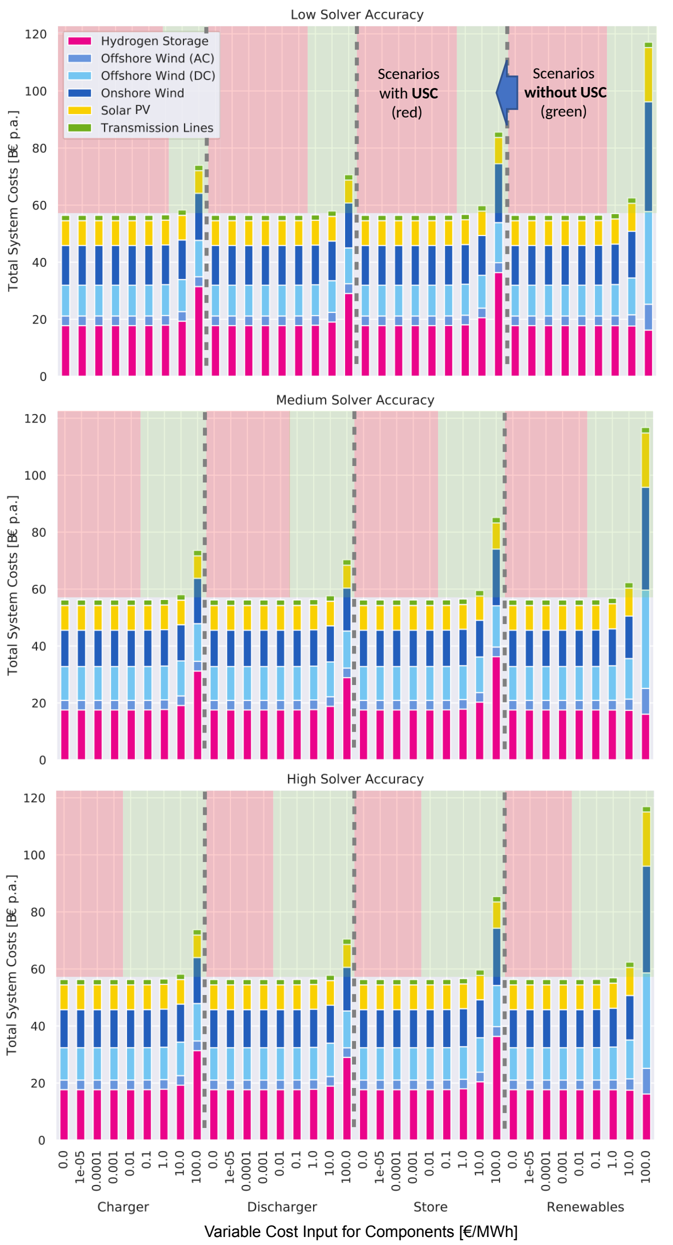


Figure 6: Total system costs for different variable cost additive scenarios. USC causes minor changes in total system cost for low to moderate cost additives. For high cost additives, total system costs increase significantly. These high variable cost beyond 10 €/MWh can significantly impact investment and operation costs and decisions. We omit illustrating total system costs from the scenarios using variable costs additives of 1000 €/MWh for readability.

equally maintained by contract based operation and maintenance. Although what might suggest variable cost differences, is the twice as much operating turbine is likely to experience on average earlier signs of fatigue in the mechanical structures and power electronics [22, 23]. As a result, the long-running turbine was indeed experiencing costs, namely, 'variable costs for lifetime reductions' which practically argues that some traditionally assumed fixed operation and maintenance costs are not fixed by nature and can indeed vary in time - for instance, when the real lifetime turbine operation is halved. Such 'variable cost for lifetime reductions' cost might be not trivial and vary from technology to technology. For instance, in the case of thermal-based processes like steam turbines, a steady rather than fluctuating operation is preferred as it reduces thermal stresses which shorten the plant lifetime [24]. As a result, even generation technologies or others bidding at currently assumed zero variable cost may experience variable costs greater than zero.

In Table 3.4, we provide a comprehensive list of variable costs for technologies that are considered as near-zero or zero variable cost devices [5, 25]. In general, variable costs are not provided in great detail [26] and, hence, should be carefully used. The limitation of such a list is that these values might not work for all models. The values are recommended for a specific modelling tool, namely PyPSA-Eur, while using the Gurobi solver with default accuracy of $BarConvTol = 1e^{-5}$, $FeasibilityTol = 1e^{-6}$. If the model, the solver or the solver parameters differ, then the suggested list might not be valid anymore. Having standardised solver parameters for specific solvers and automatic model test scripts to detect USC might help out. In contrast, one can argue that an energy system model should at least detect costs above $1/MWh$ (here recommended threshold), and that such a recommended variable cost list reduces the likeliness of USC.

## 4. Conclusion

Reliable energy system model results are essential for planning the energy transition. However, unintended storage cycling (USC), an effect that is observed in many models by simultaneous charging and discharging of the same energy storage [3], is infeasible for some technologies. It can lead to operational distortion of energy system optimization results such that full load hours of storage and renewable assets can be increased significantly (up to 23% in this study). Since, (USC) is technical infeasible for the often analysed Li-batteries, among other technologies, and can lead to significant operational distortions it should be removed.

Setting the variable costs right removes USC, while keeping the problem formulation linear and convex. But setting variable costs right is not trivial. Too low variable costs cannot be recognised by the optimization solver, which then does not guarantee the removal of USC. Very high variable cost, however, can also distort the investment and dispatch optimization results. Consequently, to avoid any model distortion it is essential to set the variable cost carefully and as accurate as possible.

We provide a list of recommended variable costs for a set of storage and renewable generation technologies extracted from

Table 2. variable cost suggestions for renewables and a set of storage technologies in energy system models based on 2030 data.

| Technology | variable cost [€/MWh] | Source |
|---|---|---|
| onshore wind | 1.4 | DEA [14] |
| offshore wind | 2.7 | DEA [14] |
| PV | $0 \rightarrow 1^{*}$ | Clauser & Ewert [27] |
| CSP[a] | 2.9 | Clauser & Ewert [27] |
| CSP + Storage | 4 | Clauser & Ewert [27] |
| biomass | 6.7 | Clauser & Ewert [27] |
| tidal | 3.1[d] | [-] |
| wave | 3.0[d] | [-] |
| geothermal | 5.6 | Clauser & Ewert [27] |
| run of river | 3.6[a,b] | EIA [28] |
| hydroelectric dams | 3.6[a,b] | EIA [28] |
| pump-hydro storage | 3.6[a,b] | EIA [28] |
| battery inverter | 6.8[a] | EIA [28] |
| battery storage | 13.5[a,c] | EIA [28] |
| hydrogen electrolyser | $0 \rightarrow 1^{*}$ | Glenk et al. [29] |
| hydrogen storage tank | $0 \rightarrow 1^{*}$ | Glenk et al. [29] |
| hydrogen fuel cell | $0 \rightarrow 1^{*}$ | Glenk et al. [29] |

[*] Reported below 1€/MWh, but set to 1€/MWh to avoid USC
[a] Interpolated between 2020 and 2035
[b] Aggregated as hydroelectric devices by EIA
[c] Assumption of cost split: 2/3 store and 1/3 inverter
[d] Assumed similar to offshore wind. Lack of reliable data [30].

recent literature. The minimum threshold for variable cost is thereby the key feature to prevent USC and reduce optimization result distortions. Quantifying the threshold for variable cost depends thereby on the solver accuracy and tolerance which make it difficult to generalise. 1 €/MWh is the threshold we found suitable for our optimization problem and default Gurobi solver accuracy settings, mainly because it does not impact the overall optimization result significantly while removing USC to a substantial degree. We further conclude that the recommended variable cost data is generally not complete, needs to be improved, and cannot remove USC in all model configurations; however at least it may significantly reduce the magnitude and likeliness of such distortions.

Moreover, setting variable costs right is expected to have great potential to remove other forms of unintended energy cycling effects. Examples are unintended energy losses through line cycling and sector cycling [3]. Both originate from the same issue, namely, that missing operational costs make it indifferent for the model to lose energy by cyclic dissipation or by curtailing energy. This merits future research on removing further effects attributed to unintended energy losses.

Let's remove the unintended cycling effect by setting the variable costs right - And let's hope that non-transparent software tools or studies do likewise.

## Code and Data availability

Code and data to reproduce results and illustrations are available on GitHub https://github.com/pz-max/unintended-storage-cycling.

## Credit authorship contribution statement

Conceptualisation: M.P., M.K.; Methodology: M.P., M.K.,; Software: M.P.; Validation: M.P., M.K.; Formal analysis: M.P. M.K.; Investigation: M.P. M.K.; Ressources: M.P., A.K.; Data Curation: M.P.; Writing - Original Draft: M.P.; Writing - Review & Editing: M.P., M.K. D.F., A.K.; Visualization: M.P.; Supervision: M.P., D.F., A.K.; Project administration: M.P., D.F., A.K.; Funding acquisition: M.P., D.F., A.K.;

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.


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## Nomenclature

### Subscript

| | |
|---|---|
| $w_t$ | Time weighting |
| $i$ | Location |
| $l$ | Line number |
| $r$ | Generator technology |
| $s$ | Storage technology |
| $T$ | optimization period |
| $t$ | Time step |

### Abbreviations

| | |
|---|---|
| $CSP$ | Concentrated solar power |
| $FLH$ | Full load hours (h) |
| $USC$ | Unintended storage cycling |
| $VRE$ | Variable renewable energy sources |

### Variable

$H^+$ Storage charge capacity (MW)

$h^+$ Storage charge (MWh)

$H^-$ Storage discharge capacity (MW)

$h^-$ Storage discharge (MWh)

$H_{i,s}^{store}$ Store capacity (MWh)

$\eta$ Efficiency

$\overline{T}$ Energy to discharging power ratio (MWh/MW)

$c$ Specific investment cost (€/MW)

$e$ Stored energy (MWh)

$F$ Transmission line capacity (MW)

$G$ Generator capacity (MW)

$g$ Generated energy (MWh)

$o$ Variable cost (€/MWh)

$w$ Weighted duration

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