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Reducing CO_2 emissions by curtailing renewables: Examples from optimal power system operation

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ABSTRACT

To lower CO_2 emissions, policy makers want to integrate as much variable renewable energy (VRE) as possible into power systems. This has been translated into targets for VRE as a share of total electricity generation and policies that aim to maximize the use of electricity available from VRE sources. However, in this paper we demonstrate that it is a misconception that maximizing VRE production always lowers CO_2 emissions. In fact there are many constraints in power system operation that can lead to situations when curtailing VRE reduces both costs and CO_2 emissions. In this paper we identify these situations and constraints, and illustrate them with several examples. The examples show how different constraints from optimal power system operation, using economic dispatch (ED) and unit commitment (UC), can combine to create the seemingly paradoxical result that curtailing VRE reduces both costs and CO_2 emissions. Broadly defined these situations can occur 1) due to network constraints which create the need for inefficient redispatch actions if VRE is not curtailed, 2) due to increased need for ramp capability and cycling from other units, and 3) due to reserve/security requirements which can be satisfied more efficiently by allowing VRE curtailment. To achieve the most economical and efficient operation of power systems, instead of VRE curtailment being seen as a measure of last resort to preserve system security, VRE should always be optimally dispatched through markets based on its true cost, thus maximizing the value of VRE to the system rather than its output.

1. Introduction

Sources of variable renewable energy (VRE), such as wind and solar, are considered to be key technologies in the transition to a carbon free and sustainable energy system. In order to reach high shares of VRE in power systems, renewable energy producers are receiving incentives to guarantee their recovery of investment costs. Usually these incentives go from investment and operational subsidies to priority access to the grid. The objective is to increase VRE production by fully dispatching VRE sources into power systems, and many countries have adopted targets for the VRE share of the total annual electricity generation.

However, with higher VRE penetration there are growing challenges to fully dispatching the VRE production into power systems, of which the main challenges are: 1) variability, 2) uncertainty, 3) nonsynchronous generation, and 4) location-specificity, where more transmission capacity is required to access the full VRE potential from different locations (Cochran et al., 2015). Note that these challenges require conventional generation to remain operational. Especially for the first 3 challenges, a significant amount of conventional generation is needed to provide flexibility to the system (usually through reserves) to face the VRE sources' variability and uncertainty as well as to ensure system security (challenge 3). That is, when there is high VRE production, units providing reserves and contributing with inertia inevitably supply part of the demand, and it may be necessary to curtail part of the VRE production. Curtailment may also be necessary if there is insufficient transmission capacity from areas with high VRE production.

Although it is accepted that some VRE curtailment is necessary to, e.g., avoid excessive expansion of transmission capacity (Klinge Jacobsen and Schröder, 2012) and maintain system security (Steurer et al., 2017), there is also a widespread belief that curtailment should be avoided if not strictly necessary for operational reasons such as those mentioned above. Curtailment is seen as inherently wasteful (Golden and Paulos, 2015) and is claimed to "increase(s) fuel use and generation-related emissions of (the) conventional power plants" (Steurer et al., 2017). Furthermore, it is argued that there is an inherent value of a "green kWh" as opposed to a "grey kWh", since the former contributes to meeting renewable targets (Höfling et al., 2015), which are set as a percentage of the produced energy in many countries.

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The view that curtailment is undesirable is also reflected in the literature on short-term power system operation such as unit commitment (UC). There is a large literature on how to incorporate the uncertainty of VRE into the UC problem (Zheng et al., 2015). However, many UC formulations do not allow VRE curtailment (Jiang et al., 2012; Jiang et al., 2013; Zhao et al., 2013; Zhao and Guan, 2016; Zhai et al., 2017; Shi et al., 2019; Alizadeh et al., 2018; Zhang et al., 2017; Sundar et al., 2019). For example, one of the most common methods for solving the UC problem with VRE uncertainty is robust optimization. Many robust UC formulations model the VRE uncertainty as a fixed uncertainty set, and thus do not allow for the possibility of curtailment to decrease either the variability or uncertainty from VRE (Jiang et al., 2012, 2013; Shi et al., 2019; Zhai et al., 2017; Zhao et al., 2013; Zhao and Guan, 2016). In other cases only the uncertainty of the residual load (demand minus VRE production) is modelled (Alizadeh et al., 2018), which also means that curtailment of VRE is not allowed. Another method to tackle VRE uncertainty is through chance-constraints, i.e., constraints that only need to be fulfilled with a certain probability, depending on the outcome of the stochastic variable representing VRE uncertainty. Many chance-constrained UC/OPF formulations also model VRE uncertainty as a fixed probability distribution, thus neglecting the possibility for VRE curtailment (Zhang et al., 2017; Sundar et al., 2019; Vrakopoulou et al., 2013; Roald and Andersson, 2018).

Contrary to these ideas, it has been shown that inflexible operation of VRE such as wind can increase system operation costs (Baldick, 2012; Ela and Edelson, 2012; Morales-España et al., 2017; Deng et al., 2015; E3, 2018). The increased costs result when constraints such as network constraints or unit commitment constraints prevent the units from being dispatched in merit order from low cost units to high cost units. Not allowing curtailment then limits the possibilities for satisfying these constraints, which can lead to an increase in costs compared to the case when curtailment is allowed. On the other hand, it is not so well known that inflexible VRE operation can also increase CO_2 emissions. To the best of our knowledge, this has been shown to occur in two studies (Deng et al., 2015; E3, 2018), and the only cause identified is increased startup emissions from conventional units (Deng et al., 2015).

In this paper, we show that there are many different situations where maximizing VRE production can lead to a simultaneous increase in both costs and CO_2 emissions. This can occur not only due to more frequent startups and shutdowns of units, as discussed in (Deng et al., 2015), but also due to network constraints, ramping requirements, minimum uptime requirements or reserve/security constraints, all of which affect the mix of online units.

A common market setup for power system operation includes a day-ahead market which solves a UC problem or similar to determine the online/offline status of units for the next day and an economic dispatch (ED) to find the optimal production set points of the units which have been scheduled to operate, ED is also commonly used to clear real-time markets (FERC, 2014). In this paper, we provide several examples of situations where curtailing VRE simultaneously reduces costs and CO_2 emissions, for both ED and UC problems. For the ED, we show that either 1) network constraints or 2) ramping constraints can, by themselves, create such situations. For the UC, the presence of minimum outputs in combination with 3) startup costs or 4) minimum up/down times is sufficient. Furthermore, when solving a 5) stochastic UC with wind uncertainty, or 6) a UC with N-1 security constraints, it is also possible to have situations where VRE curtailment leads to decreased costs and CO_2 emissions.

The examples presented here use data for costs and emissions of units taken from Deng et al. (2015). However, similar results can be found for units with different characteristics, as long as there are constraints such as network constraints, unit commitment constraints, or reserve requirements that constrain the dispatch. These types of constraints are present in all power systems and are incorporated in market clearing algorithms in increasing detail, since they are needed to guarantee that the market solution will result in a technically feasible dispatch of units (although the degree to which technical constraints are considered vary between different markets). For example, the European market clearing algorithm EUPHEMIA considers simplified transmission constraints based on a zonal model and allows block bids that respect the minimum production level of units and span several time periods, thus respecting the units' minimum uptime (NEMO, 2020). On the other hand, most of the markets in the US operate by solving UC and ED problems (FERC, 2014).

Additionally, we show that, for all the examples, using a regression model to estimate the marginal change of CO_2 emissions with increased wind production gives misleading results. Such regression models are commonly used to estimate the efficiency of VRE in decreasing CO_2 emissions (Kaffine et al., 2013; Amor et al., 2014; Novan, 2015; Oliveira et al., 2019), but our results show that, for these examples, they are not able to capture the dynamics of power systems, such as the inter-dependence between different time periods, and the binary nature of the commitment decisions.

Thus the main contributions of this paper are:

1. We demonstrate that it is a misconception that increasing VRE production always decreases CO_2 emissions. For this purpose we identify the situations and constraints present in power systems that lead to situations with the paradoxical result that curtailing VRE production simultaneously reduces both costs and CO_2 emissions. We show that these situations can occur not only due to more frequent unit startups, as noted in (Deng et al., 2015), but also due to network constraints, ramping requirements, minimum uptime requirements or reserve/security constraints, all of which affect the mix of online units. We illustrate these situations using stylized examples from power system operation (UC and ED).
2. We also show that, for these examples, econometric regression analysis does not capture the inter-dependencies in power system operation, thus giving misleading conclusions with regard to the marginal effect of increased VRE production on CO_2 emissions.

The remainder of this paper is organized as follows: Section 2 gives examples of the ways in which VRE is forced into the grid in European power systems, considering both renewable support mechanisms and market data. Section 3 presents examples of when curtailing VRE can decrease both costs and CO_2 emissions, and Section 4 applies regression analysis to the results. Section 5 discusses and draws general conclusions from the examples, and Section 6 concludes.

2. Ways of forcing renewables into the grid

There are different ways in which VRE is forced into the grid, without considering whether this is the most efficient way to operate the system in terms of costs and CO_2 emissions. The main mechanisms are: 1) subsidies to VRE that incentivice negative bidding and thus avoid curtailment, 2) giving priority dispatch to VRE during system operation, i.e., only curtailing VRE after all options for curtailing conventional generation have been exhausted, and 3) having VRE installations which are insensitive to market signals such as behind-the-meter installations or installations where curtailment is not technically possible. In this section we give examples of these mechanisms, with focus on European power systems.

2.1. Renewable support schemes

The most straightforward VRE support scheme is the feed-in-tariff, which guarantees VRE producers a fixed price for their energy production. VRE producers receiving a pure feed-in-tariff will never volontarily curtail their production, irrespective of what the market prices are. Feed-in-tariffs are still common for small-scale VRE, e.g., in both Germany and France where PV plants smaller than 100 kW receive this subsidy (EU, 2021).

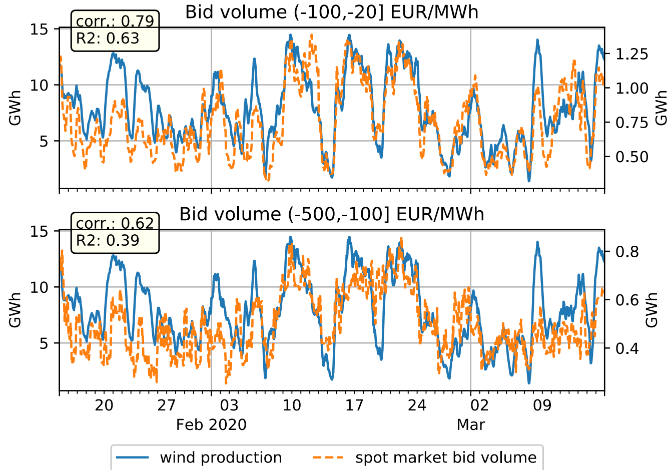

Fig. 1. Evidence of negative bidding by wind in the Nordpool market from 2020. Solid line shows aggregate wind generation (left axis) and dashed line shows the total volume of spot market bids (right axis) in the range (−100,−20] EUR/MWh (top) and (−500,−100] EUR/MWh (bottom).

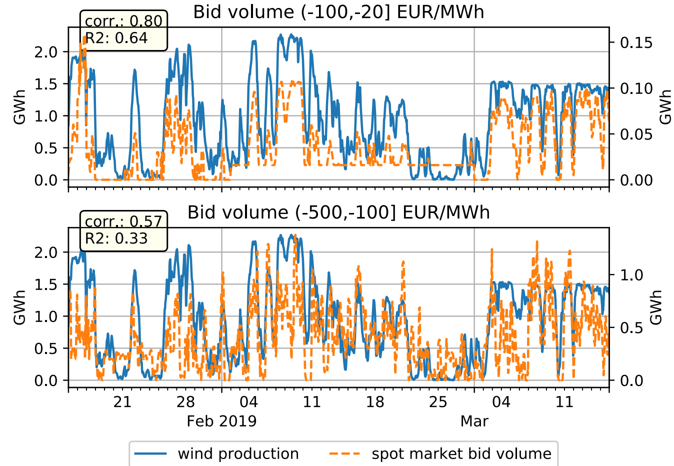

Fig. 2. Evidence of negative bidding by wind in the Netherlands from 2019. Solid line shows aggregate wind generation (left axis) and dashed line shows the total volume of spot market bids (right axis) in the range (−100,−20] EUR/MWh (top) and (−500,−100] EUR/MWh (bottom).

For large scale VRE the most common support mechanisms are some form of energy subsidies (Banja et al., 2017; EC, 2019). Although VRE producers receiving these subsidies are participating in electricity markets, they have an incentive to produce even at negative electricity prices, thus reducing curtailment compared to if they were dispatched according to their true production cost. These support mechanisms include both feed-in-premiums such as those in Germany and the UK (Huntington et al., 2017) and flat energy-subsidies such as the electricity certificates used in Sweden and Norway (Banja et al., 2017). Some energy subsidies, such as the SDE+ support scheme in the Netherlands (RVO, 2021), give very similar incentives to feed-in-premiums, since they almost completely compensate the losses incurred by VRE producers during periods of negative prices. However, in some countries such as the Netherlands and Germany, energy subsidies are not given if prices are negative for more than 6 consecutive hours (Höfling et al., 2015; RVO, 2021).

In the following analysis of market data, we show that VRE flexibility is indeed withheld from the market in European power systems. Although bids submitted to European electricity markets are anonymous, it is possible to infer the behaviour of VRE production such as wind from the aggregated bid curves (which are available). Figs. 1-2 show the negative bidding by wind power for the Nordic market (Fig. 1) and for the Netherlands (Fig. 2). The figures show, for each hour, the volume of all bids within a certain price range together with the aggregated wind production, as well as the Pearson correlation coefficient and R^2 value when the bid volume is regressed against the wind power production. The strong correlation between the time series clearly indicates that the bids consist mainly of wind power[2]. Surprisingly, there seems to be a significant amount of wind power that is bidding below −100 EUR/MWh, both in the Nordpool market area and in the Netherlands. In the Netherlands this may be motivated by the SDE+ support scheme which is a form of feed-in-premium (RVO, 2021). For Nordpool, which consists of several countries with different VRE support schemes, it is not clear if this bidding is motivated by VRE subsidies or if it is related to operational strategies of wind producers. For example, it may be that a wind producer considers the risk of incurring a substantial loss due to negative prices so low that it is better to bid close to the price floor and thus ensure being dispatched, to avoid having to be prepared to curtail its production.

[2] Notice that a perfect correlation cannot be expected, since the bids made in the day ahead market contain forecast errors.

2.2. Priority dispatch

During times when curtailment is necessary, market prices may induce VRE to self-curtail if prices become sufficiently low (negative). However, often it can happen that the need for curtailment is not seen by the market, either due to forecast errors that become apparent first close to real-time, or if curtailment is necessary due to, e.g., grid congestion or security reasons not considered in the market clearing. In such situations system operators will have to make the choice of which units to curtail. Often in these situations VRE has priority to be dispatched. For example, in Germany it is mandated by law that VRE curtailment is only allowed if the issues creating the need for curtailment (grid congestion or severe threats to system reliability) cannot be solved by curtailing conventional generation (Brandstätt et al., 2011; BMWi, 2017). By EU law, all VRE commissioned before 4 July 2019 or VRE with a capacity below 400 kW is subject to priority dispatch (EC, 2019), meaning it will be curtailed after conventional generation.

2.3. Behind-the-meter generation

Significant amounts of VRE, particularly solar, is installed behind-the-meter in private homes and commercial buildings, which means that the production of these VRE plants is not directly monitored by the TSO/DSO. For example, in California there was estimated to be 6.2 GW of behind-the-meter solar PV capacity in 2018 (CAISO, 2018). Such generation is mostly price-insensitive, as the plant owner is not exposed to market prices. Also, most such plants are small scale and may not have the technical capability, such as remote control, to perform dynamic curtailment. For example, the European grid code does not require power plants smaller than 1 MW to be able to be operated remotely, although it is possible for TSOs to require remote turn-off capability (EC, 2016). In Germany, 52% of all solar capacity, or 22 GW, is installed in PV-systems with less than 100 kW capacity (Wirth, 2020).

3. Examples of decreased emissions by curtailing renewables

Here we provide examples of how different constraints in both UC and ED can create a situation when curtailing VRE simultaneously decreases costs and CO_2 emissions. Examples 1–2 are versions of ED and Examples 3–6 are UC problems, thus including commitment decisions and minimum outputs of units. Notice that the examples can be valid also for power systems that do not explicitly operate by means of UC and ED. For example, also the European day-ahead market clearing

Table 1
Generator units.

Type	Fuel	Max prod. (MW)	Min prod. (MW)	Max ramp (MW/h)	Min up time (h)	Min down time (h)	Startup cost ($)	Startup CO_2 emis. (ton)	Marginal cost ($/MWh)	Marginal CO_2 emis. (ton/MWh)
ST	Coal	200.0	80.0	80.0	3	2	48,879.0	1035.0	38.8	0.824
CCGT	Natural gas	300.0	120.0	120.0	3	3	15,671.0	190.0	27.7	0.337
CT	Natural gas	150.0	50.0	100.0	1	1	18,687.0	49.0	69.6	0.844
Wind	–	–	–	–	–	–	0	0	0	0

Types: ST - Steam turbine, CCGT - Combined cycle gas turbine, CT - Combustion turbine (single cycle).

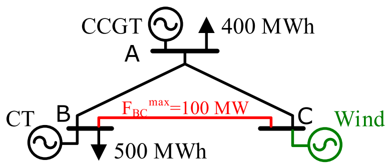

Fig. 3. Three bus network with the CCGT connected to bus A, the CT to bus B, and the wind farm to bus C. All lines are assumed to have the same reactance, e.g., 1 Ω.

algorithm EUPHEMIA includes unit-commitment constraints such as minimum generation levels (NEMO, 2020), and solving an ED may be used to simulate the optimal re-dispatch of units in a real-time or imbalance markets.

The examples are based on the generator units shown in Table 1. The costs and emissions of the units are taken from (Deng et al., 2015), assuming a CO_2 price of $25/ton. Notice that wind power production is completely flexible within the range given by the available production, which varies for the different examples. This is motivated by the technical capabilities of VRE such as wind farms and PV solar farms, which allow them to operate very flexibly within the bounds set by the maximum available production (Faiella et al., 2013; NREL, 2017). See Appendix A for the complete ED and UC formulations, and Appendix B for the load and wind data.

3.1. Network constraints

This example solves an optimal dispatch for one time period, i.e., an optimal power flow (OPF) with DC network constraints. The network is shown in Fig. 3. Only the generators CCGT and CT are included, and they are both assumed to have maximum output 1000 MW (different from those in Table 1) and minimum output 0 MW. Additionally there is a wind generator which can produce a maximum of 345 MWh. The total demand of the system is 900 MWh.

Table 2 shows the results obtained both when forcing wind and when optimally dispatching wind. Due to the congestion of line BC (in direction from C to B), the units cannot be fully dispatched from cheaper to expensive, that is, to obtain a feasible solution and not overload the line BC. When imposing that wind must be completely dispatched, the most expensive unit (CT) needs to produce 545 MWh and the next cheaper unit (CCGT) can only produce 10 MWh. If we allow the wind to be optimally dispatched, by curtailing it as long as it reduces costs and CO_2 emissions, 100% of the wind is curtailed resulting in a reduction of costs and CO_2 emissions by 12.9% and 12.6%, respectively.

This counter-intuitive result can be explained as follows: starting from the solution when wind is fully dispatched (and line BC is congested), suppose the load at bus C is increased by 1 MW. To find the marginal price at bus C we want to know what the cheapest redispatch is that can supply this load. The cheapest way to do this is to increase production by CCGT by 1 MW. This will increase the flow on BC (from B to C) by 1/3 MW, thus making the line BC less congested than before. Since BC is less congested, CCGT can increase its production additionally by 1 MW, while CT decreases its production by 1 MW. This second transaction decreases the flow on BC by 1/3 MW so that it is once more fully congested. The total cost of the redispatch is 2MWh · 27.7$/MWh − 1MWh · 69.6$/MWh = − 14.2$, i.e., a decrease of the total costs by 14.2$. Thus the locational marginal price (LMP) at bus C is −14.2$/MWh (formally obtained from the dual variables). Similarly the marginal CO_2 emissions at bus C are −0.17 ton/MWh, meaning that additional wind power production at bus C increases emissions. As long as CT is producing and line BC is congested, it will be beneficial to curtail wind power, which results in all wind power being curtailed. Thus this example shows that just network constraints, by themselves, can create a situation when curtailing wind power decreases both costs and CO_2 emissions. A similar example showing that curtailing wind power can reduce costs, but without any analysis of the impact on CO_2 emissions, can be found in (Ela and Edelson, 2012).

Table 2
Results from DCOPF with network constraints.

	Gen. [MW]		Cost [$]		CO_2 [ton]	
	Forced	Optimal	Forced	Optimal	Forced	Optimal
CCGT	10	700	277	19,390	3.37	235.9
CT	545	200	37,932	13,920	459.98	168.8
Wind	345	0	0	0	0	0
Total	900	900	38,209	33,310	463.35	404.7
Avg. [1/MWh]	–	–	42.5	37	0.515	0.45
Diff. [%]	–	–	–	−12.9	–	−12.6

3.2. Ramping constraints

The example of this section shows how wind dispatch can help to increase the ramp capabilities of the system, thus increasing its flexibility. This example consists of three units, a wind unit and the two generating units CCGT and CT, which must supply the demand shown in Fig. 4. Minimum ouput levels are not considered and wind can provide a steady supply of 100 MWh for all periods. When wind is forced to produce its maximum possible output for all the periods, the optimal dispatch for

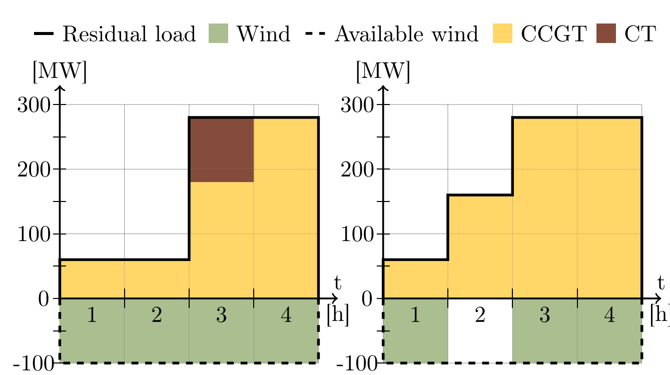

Fig. 4. ED with ramp constraints: forcing wind (left) and optimally dispatching wind (right).

Table 3
Results from ED with ramp constraints.

	Gen. [MW]		Cost [$]		CO_2 [ton]	
	Forced	Optimal	Forced	Optimal	Forced	Optimal
CCGT	580	780	16,066	21,606	195.46	262.86
CT	100	0	6960	0	84.4	0
Wind	400	300	0	0	0	0
Total	1080	1080	23,026	21,606	279.86	262.86
Avg. [1/MWh]	–	–	21.3	20	0.259	0.243
Diff. [%]	–	–	–	−6.1	–	−6.2

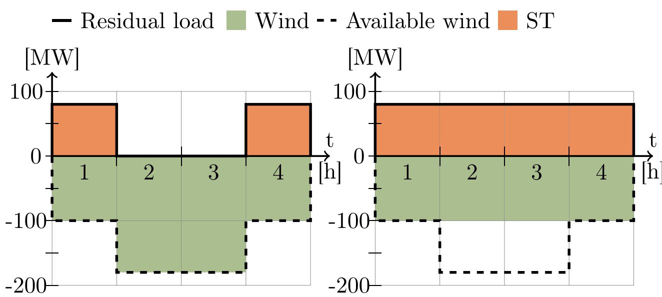

Fig. 5. UC with startup costs: forcing wind (left) and optimally dispatching wind (right).

Table 4
Results from UC with startup costs.

	Gen. [MW]		Cost [$]		CO_2 [ton]	
	Forced	Optimal	Forced	Optimal	Forced	Optimal
ST	160	320	55,087	12,416	1166.84	263.68
Wind	560	400	0	0	0	0
Total	720	720	55,087	12,416	1166.84	263.68
Avg. [1/MWh]	–	–	76.5	17.2	1.621	0.366
Diff. [%]	–	–	–	−77.5	–	−77.4

the remaining units is to dispatch the next more expensive unit CCGT (60 MWh), thus covering the demand completely for the first two hours, and then increasing its production to 180 MWh by ramping up at its maximum ramping capability (120 MW/h). However, since the CCGT cannot cover the complete demand ramping requirement of 220 MW/h, then the CT has to provide the ramping and energy deficit of 100 MWh in hour 3.

Table 3 shows the total cost and emissions of this example. When forcing wind the marginal prices and emissions for hours 1 and 4 are set by the marginal unit CCGT, and for hour 3 the marginal values are set by the marginal unit CT. However, for hour 2 the marginal price and emissions are −14.2 $/MWh and −0.17 ton/MWh, respectively. Similarly to the previous example, these negative marginal costs (emissions) appear because an additional unit of load at hour 2 would be supplied by the CCGT also allowing to increase its production at hour 3 by 1 unit, which in turn would reduce the production of the CT by 1 unit. Consequently, the CCGT provides additional energy for both hours 2 and 3, delivering 2 additional MWh in total, while the electricity output of the CT is reduced by 1 MWh. The marginal cost of this 1 MWh increased demand, or wind reduction, at hour 2 is then $2 \cdot 27.2 - 69.6 = -14.2$$/MWh, and the marginal emissions are $2 \cdot 0.337 - 0.844 = -0.17$ ton/MWh. Thus increasing wind production (or decreasing load) at hour 2 increases costs and CO_2 emissions.

On the other hand, by optimally dispatching wind, the ramping capability of the system increases, that is, wind is now supplying ramp-up flexibility to the system. As shown in Fig. 4, wind is optimally dispatched (curtailed) during the second hour, allowing wind to supply a 100 MW ramp from hour 2 to 3, thus lowering the (residual) ramping needs of the system and completely replacing the flexibility previously provided by CT. Table 3 shows that although there is 25% less wind production, the total costs and emissions are lowered by 6%, compared to the case without curtailment.

Notice that this example is similar to the famous case of the "duck curve" in California (NREL, 2015), when the evening load peak combines with decreasing PV output to produce a very steep increase in the residual load (demand minus VRE production).

3.3. Startup costs and minimum output

This example includes just two generators, the ST and wind, which together should supply a constant load of 180 MW for 4 h. For the ST we include min/max output constraints, production and startup costs as well as production and startup emissions. The unit is assumed to be online at the start of the period, thus not incurring startup costs and emissions for the first hour. The potential wind generation is as shown in Fig. 5. If all available wind power is dispatched, the ST needs to shut down in period 2 and start up again in period 4, see Fig. 5. Total costs and emissions are shown in Table 4, where more than 87% of costs and emissions result from the additional startup. If, on the other hand, wind can be curtailed the optimal schedule is to curtail enough wind during period 2–3 to allow the ST to remain online, thereby avoiding a startup of this unit. Table 4 shows that curtailing 29% of available wind generation results in a reduction of costs and emissions by 77%.

3.4. Minimum uptime and minimum output

Here, apart from wind, we consider the CCGT and ST units and all constraints (however, for this example, only the minimum up time

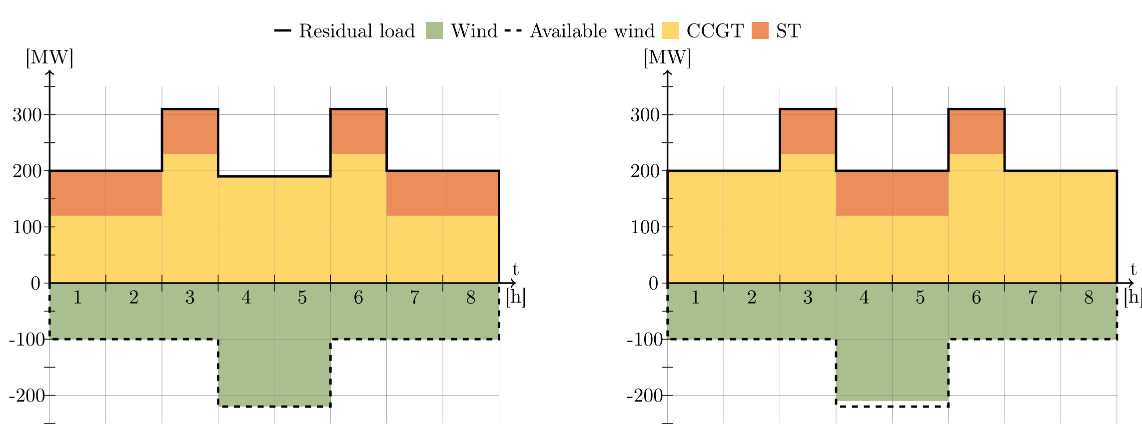

Fig. 6. UC with minimum up time: forcing wind (left) and optimally dispatching wind (right).

Table 5
Results from UC with minimum up time.

	Gen. [MW]		Cost [$]		CO_2 [ton]	
	Forced	Optimal	Forced	Optimal	Forced	Optimal
CCGT	1320	1500	36,564	41,550	444.84	505.5
ST	480	320	116,382	61,295	2465.52	1298.68
Wind	1040	1020	0	0	0	0
Total	2840	2840	152,946	102,845	2910.36	1804.18
Avg. [1/MWh]	–	–	53.9	36.2	1.025	0.635
Diff. [%]	–	–	–	−32.8	–	−38

Table 6
Results from stochastic UC when forcing wind production.

	Gen. [MW]		Cost [$]		CO_2 [ton]	
Scenario	1	2	1	2	1	2
CCGT	0	0	0	0	0	0
ST	0	0	0	0	0	0
CT	860	1200	78,543	102,207	774.84	1061.8
Wind	1140	800	0	0	0	0
Total	2000		90,375		918.32	
Avg. [1/MWh]	–		45.2		0.459	

and minimum output are binding). It is assumed that the CCGT was already online at the beginning of hour 1 and the ST was offline. Fig. 6 shows the optimal dispatch of the units and Table 5 uptime shows the resulting costs and emissions. Note that the residual load for hours 3 and 6 is 310 MWh, which is higher than the maximum output of the CCGT, hence the ST is needed. To balance supply and demand when forcing wind, the ST must be turned off during hours 4 and 5 because the minimum outputs of the ST (80 MW) and the CCGT (120 MW) exceed the residual load during these periods (190 MWh). Therefore, when fully dispatching the wind power, the ST must be started up twice to supply the demand for hours 3 and 6. Moreover, the minimum up time of the ST also forces it to be producing from hours 1 to 2 and from 7 to 8, thus reducing the output of CCGT, the cheaper and less polluting unit, to accommodate the minimum output of the more expensive and polluting ST during these periods. On the other hand, if wind is optimally dispatched, the ST then produces during 4 periods instead of 6 and has one startup instead of two, as shown in Fig. 6. By curtailing just 2% of the available wind power, costs and emissions are reduced by 33% and 38%, respectively.

Notice that the cost and emissions shown here include contributions from the startup process. However, solving the problem without considering startup costs gives the same production schedules, with a reduction (though smaller than before) in both costs and emissions in the case when wind power is curtailed. Thus the combination of minimum output and minimum uptime requirements, by themselves, is enough to create a situation where costs and CO_2 emissions can be decreased by wind curtailment.

3.5. Wind uncertainty and minimum output

This example is solved using stochastic optimization to optimally schedule the dispatch of units to accommodate variations in wind power and its expected uncertainty. In this example all three units are considered with all of their constraints, and all units are assumed to be offline initially. Two possible wind scenarios with equal probability of occurrence are considered, as shown in Fig. 7. To face this wind uncertainty, a set of units must be committed in advance to accommodate any of the two wind scenarios while balancing generation and demand. This can be seen as if the committed units must have sufficient reserves to balance the wind generation, although the reserves are not modelled explicitly in the stochastic optimization problem. Thus here we consider the main two-stage decisions that take place in power systems, where the first stage represents the day-ahead planning of which units should be online and the second stage optimally dispatches the online units in response to the realized wind uncertainty, as in, e.g., real-time and imbalance markets.

If wind curtailment is not allowed, the other units that are committed must have the flexibility to supply the residual load, which is between 70 MWh and 150 MWh. The only unit able to supply this residual load is the CT, because the others have a higher minimum output. The optimal solution is then presented in Table 6, where the CT is

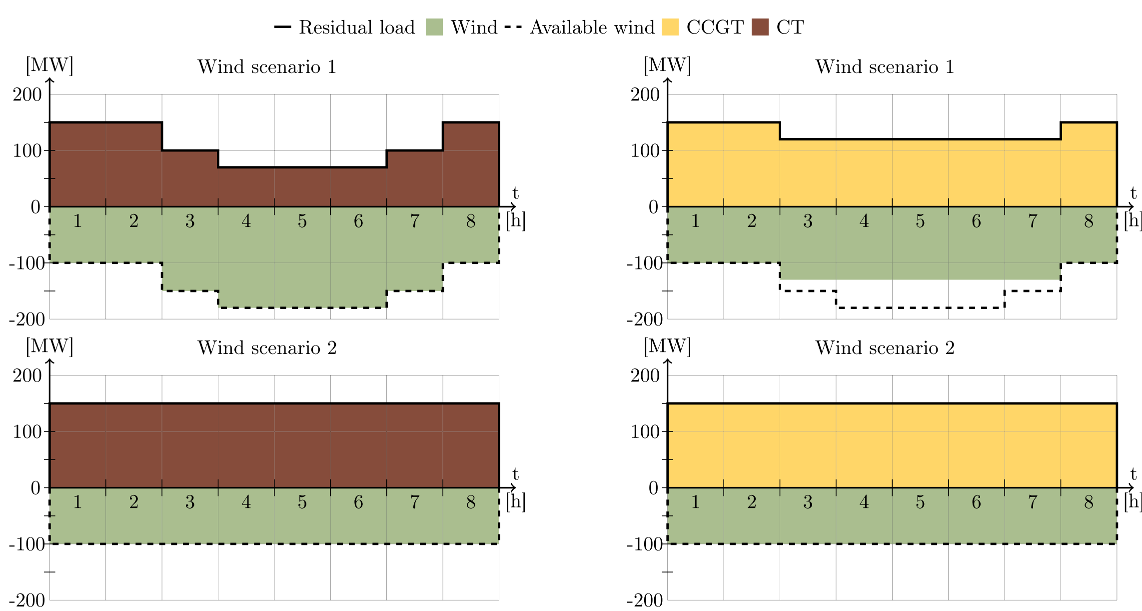

Fig. 7. Stochastic UC with wind uncertainty: forcing wind (left) and optimally dispatching wind (right).

Table 7
Results from stochastic UC when optimally dispatching wind.

	Gen. [MW]		Cost [$]		CO_2 [ton]	
Scenario	1	2	1	2	1	2
CCGT	1050	1200	44,756	48,911	543.85	594.4
ST	0	0	0	0	0	0
CT	0	0	0	0	0	0
Wind	950	800	0	0	0	0
Total	2000		46,833.5		569.125	
Avg. [1/MWh]	–		23.4		0.285	

Table 8
Results from UC with N-1 security.

	Gen. [MW]		Cost [$]		CO_2 [ton]	
	Forced	Optimal	Forced	Optimal	Forced	Optimal
CCGT	0	960	0	26,592	0	323.52
CT	400	0	27,840	0	337.6	0
ST	720	640	27,936	24,832	593.28	527.36
Wind	1280	800	0	0	0	0
Total	2400	2400	55,776	51,424	930.88	850.88
Avg. [1/MWh]	–	–	23.2	21.4	0.388	0.355
Diff. [%]	–	–	–	−7.8	–	−8.5

the only scheduled unit, even though it is the most expensive and polluting unit. On the other hand, by optimally dispatching wind, the most economic unit, the CCGT, can be scheduled instead, and the optimal results are shown in Table 7. In this case, wind lowers its production, thus offering flexibility to the system and not leaving all the flexibility demands to the other units. By allowing wind to provide flexibility, the total costs and emissions are lowered by 48% and 38%, respectively.

3.6. N-1 security and minimum output

In this example all units in Table 1 are considered and must supply a constant load of 300 MW together with the wind production shown in Fig. 8. Additionally, the UC formulation in this example also includes N-1 security constraints, i.e., a common security requirement that ensures that if anyone of the online units (including the wind generator) is lost due to an outage, the remaining online units have enough reserves to make up for the lost production. In this example only conventional units are able to provide reserves. This means that at least two conventional units need to be online, so that in case one of them fails the other one can cover the lost production. It is assumed that whichever units are scheduled in the first period they have been online since previously, i.e., startup costs are not imposed in the first hour.

Table 8 shows the costs and emissions resulting from the optimal commitment schedules. If all wind power is dispatched, the optimal schedule uses the ST and the CT. Although the CCGT is more economical than both the ST and the CT, it is not possible to schedule this unit because the residual load is too low to allow simultaneous operation of the CCGT together with another unit.

However, if wind can be curtailed, it is possible to lower wind generation enough to allow the CCGT to replace the CT in the operation schedule. This curtailment of 33% of available wind power results in a reduction of costs by 8% and emissions by 9%, as shown in Table 8. Notice that in this formulation there is no cost for conventional units to provide reserves. However, if this were the case, allowing wind curtailment would allow the wind unit to provide reserves and thus further reduce the cost, as the curtailed wind power could replace some reserves held by other units.

4. Regression analysis of CO_2 emissions

A common method to assess how much VRE such as wind power decreases CO_2 emissions is regression analysis (Kaffine et al., 2013; Amor et al., 2014; Novan, 2015; Oliveira et al., 2019). Assuming time series data for CO_2 emissions is available, this data can be regressed against the wind power production using multivariate regression. In addition to wind power production these regression models commonly include demand data (included with different powers to capture non-linear effects) and fixed effects for different time periods (Novan, 2015; Oliveira et al., 2019).

We can apply a similar analysis to examples 2–6 which span several time periods. Fig. 9 shows a simple regression of CO_2 emissions on the wind power production, for Example 3 when forcing the maximum wind production. The data points with 100 MWh wind production correspond to period 1 and 4 with the highest costs and CO_2 emissions and period 2 and 3 are seen as the point to the right with zero CO_2 emissions. The obtained coefficient suggests that each extra MWh of wind power

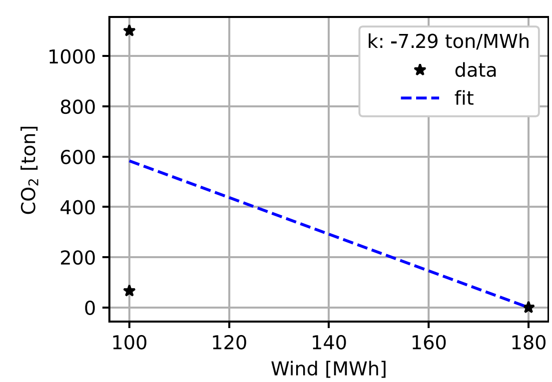

Fig. 9. Regression of CO_2 on wind power for example 3 with startup costs.

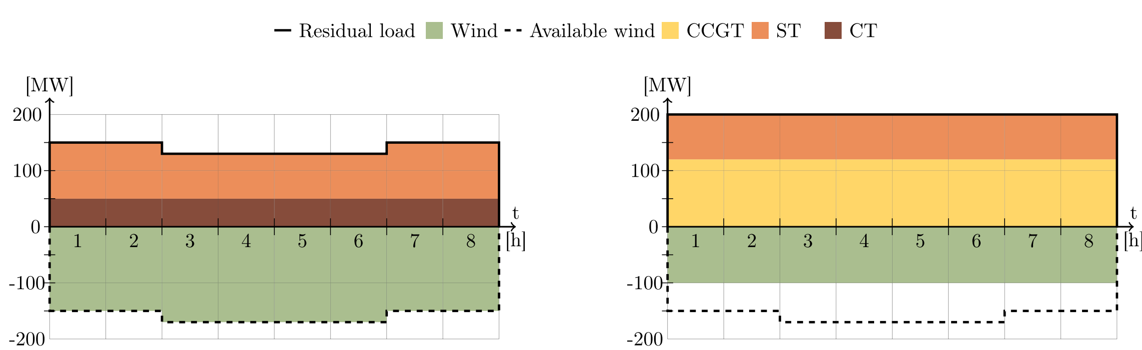

Fig. 8. UC with N-1 security: forcing wind (left) and optimally dispatching wind (right).

Table 9
Coefficients for regression of CO_2 emissions on wind power for the examples.

	k [ton/MWh]
2 Ramp	−0.45
3 Startup	−7.29
4 Min uptime	−3.68
5 Stochastic	−1.06
6 N-1 security	−0.82

reduces CO_2 emissions by 7.29 ton.[3] However, as shown in the example CO_2 emissions can in fact be reduced by almost 80% by curtailing 1/3 of the available wind generation, and thus avoiding an extra startup of the coal unit. Also, a marginal increase of available wind power in period 1 and 4 will not reduce either costs or CO_2 emissions, since the ST is already producing at its minimum output level. Notice that since demand is constant, the same result would also be obtained using multivariate regression and incorporating demand as an explanatory variable.

Table 9 shows the coefficients, obtained similarly, for Examples 2–6. For the examples which do not have constant demand (Example 2 and 4), the demand was made constant (380 MWh and 400 MWh, respectively) and the wind production was changed to give the same residual load as in the original examples. This yielded the same dispatch of the conventional units for the cases when forcing and optimally dispatching wind, and thus also the same costs and CO_2 emissions. For all examples, the regression suggests that more wind will decrease CO_2 emissions, when in fact the opposite is true, that optimally curtailing wind will decrease CO_2 emissions. The results also hold under a multivariate regression including demand, as this is constant.

The reason for the results is that a regression model is not able to capture the non-linear and time-coupled effects that exist in power systems. For example 3, the regression model cannot see that wind production in period 2 and 3 is causing a large increase of CO_2 emissions in period 4 as the coal unit ST has to start up. Similarly, for example 2, the regression does not capture that reducing wind power can decrease the ramp of the net load between hour 2 and 3, thus avoiding the use of the polluting CT. Notice that this last example is a an ordinary linear programme (LP), meaning that all variables are continuous and all constraints linear, but the regression still gives misleading results.

5. Discussion

In Section 3 we presented examples from ED and UC problems when curtailing wind power can simultaneously decrease costs and CO_2 emissions. Although each example involves a specific set of constraints that gives rise to the situation where curtailment is beneficial, we can identify three broad categories of reasons:

1. Curtailing due to network constraints, as seen in Example 1. Curtailing can sometimes be the most efficient way to alleviate network constraints, and not curtailing can create a need for redispatching conventional units in such a way that the total emissions of the system increases.
2. Curtailing to decrease the need for cycling of other units, as seen in Examples 2–4. The reduced cycling can be achieved by reducing system ramp requirements and avoiding the use of fast-ramping units (Example 2) or reducing the number of startups/shutdowns of conventional units due to more efficient ways of satisfying minimum production levels (Example 3) and minimum up-times (Example 4).
3. Curtailing to satisfy reserve requirements more efficiently, as in Examples 5–6. Curtailing renewable generation can decrease the range of upward and downward reserves needed to face wind uncertainty (Example 5) or for providing N-1 security (Example 6) and thus allow reserve requirements to be met by cheaper and less polluting units.

Notice that similar results can be obtained for different types of units. For example, the unit CCGT may be replaced with a biomass unit with the same cost and technical characteristics but zero emissions. This will give the same dispatch results for all examples but further increase the reduction in CO_2 emissions achieved with flexible operation of wind power, as the difference in CO_2 emissions between the biomass unit and the more polluting conventional units will be even larger. Also, all examples in Section 3 give exactly the same results if the CO_2 emissions are minimized instead of the operation costs. This is not surprising, as the costs are correlated with the CO_2 emissions due to the inclusion of CO_2 prices in the variable costs. A dispatch that maximizes social welfare can also lead to a minimization of CO_2 emissions, if VRE is dispatched in a flexible manner, thus maximizing its value to the system.

The examples in this paper do not consider the possibility of using renewables to provide reserves, but doing so would further increase the value of VRE flexibility, as curtailed generation can be used for providing reserves (Dvorkin et al., 2015; Hedayati-Mehdiabadi et al., 2015). Actually, many European grid codes require large scale VRE to be curtailable, and specify requirements for active power frequency control to allow VRE to provide primary frequency reserves (Nycander and Söder, 2018). Generally, both large scale PV and wind power have excellent capabilities to provide ancillary services that require either active or reactive power control (providing spinning reserves, load following, voltage control, frequency regulation, etc.), and actually perform better than conventional generators in some respects (Faiella et al., 2013; NREL, 2017). Wind power also has the possibility to provide synthetic inertia, which would lower the need for conventional generation to remain operational, thereby reducing another source of inflexibility in the system (Fernández-Guillamón et al., 2019). For an overview of the use of VRE to provide reserves in practice in European and U.S. electricity markets, we refer to (Edmunds et al., 2019; Ela et al., 2011).

An important question is to what extent the results shown for the examples in this paper can be generalized to larger, more realistic systems. Deng et al. (2015) have shown, using test systems with 9–16 units and different compositions of thermal and nuclear generators, that CO_2 emissions can increase by about 1.5% as curtailment penalizations increase from 0$/MWh to 300$/MWh. However, they omit network constraints, and it is possible that having a high concentration of VRE in a certain part of the network, as is often the case in real systems, can increase the negative impacts of not curtailing, as units have to be redispatched to satisfy transmission constraints, as shown in Example 1. The effect of inflexible VRE operation on CO_2 emissions will also depend on factors such as the system size, the level of VRE penetration, and the CO_2 price. The latter is investigated in Deng et al. (2015) with the result that the effect of the CO_2 price depends strongly on the power system that is considered.

Some of the examples in this paper can be thought to be less relevant for larger test systems. The results in Examples 5 and 6 occur since there is only a small number of conventional units with different minimum output levels, so that a relatively small change in the wind power dispatch can change which units are scheduled to be online. For a larger test system, the number of combinations of other units increases exponentially, so it may be thought that the impact on CO_2 emissions will be smaller. On the other hand, there can also be other constraints, e.g., network constraints, which limit the choices of online units. In general, if there are no technical constraints on the system, then VRE should be dispatched fully, since it has zero marginal cost and thus comes first in the merit order dispatch. The more constraints that are added to the UC and ED problems, to reflect a more realistic operation, the higher the probability that the merit order dispatch cannot be realized, and that it

[3] The high value is due to the start-up emissions in period 4, resulting in a large amount of CO_2 emissions even though the unit is only producing 80 MWh for one hour. In general, since the examples are stylized and consider only a few units for a short time period the magnitude of the CO_2 emissions is not representative of real systems.

may be necessary to curtail VRE. Thus, we believe that more studies on realistic test systems will be necessary to determine to what extent the effects shown in this paper are relevant in real power systems.

There are several studies that investigate the emission increases in actual power systems resulting from increased flexibility requirements from conventional units due to more VRE. While some studies find that these emission increases are small compared to the emission reductions due to the displaced energy (NREL, 2013; Clancy et al., 2015), there are also studies which show that flexible VRE generation can decrease CO_2 emissions in real systems for high VRE penetrations (E3, 2018).

Another question is how relevant the results are for future low carbon power systems. As mentioned before, the examples remain valid if the CCGT unit is replaced with an identical unit which has zero CO_2 emissions (e.g., a nuclear or hydrogen-fired power plant). The implication of this is that as long as there is a single polluting technology remaining, inflexible VRE operation can force the use of the polluting technology, thereby increasing CO_2 emissions. If there are network constraints, as in Example 1, or ramping constraints for the low- or non-polluting technologies, as in Example 2, these constraints can then force the use of the polluting unit(s). The situation in Example 4 and 5 can also occur, if the low- or non-polluting technologies have constraints such as minimum output levels and minimum up/down-times. Many technologies which may come to play an important part in a future low-carbon power system have these type of constraints, e.g., nuclear power (Helistö et al., 2020), conventional power plants with carbon capture and storage (Brouwer et al., 2015; Szima et al., 2019; Oates et al., 2014), and also from the demand side, such as electrolysis for hydrogen production (Gabrielli et al., 2018). Thus, as long as the power system is not completely CO_2 free we believe that flexible VRE operation will be important to minimize the costs and emissions from its operation.

The results presented here have implications for methods for power system operation with significant VRE penetration, for VRE support policies, and for assessing CO_2 reductions from VRE.

Regarding research on power system operation using UC and ED, there is a large litterature aimed at improving existing methods to consider VRE uncertainty (Zheng et al., 2015). As mentioned in the Introduction, many formulations inherently consider the VRE uncertainty as arising from a fixed probability distribution, whether these are robust formulations (Jiang et al., 2012; Jiang et al., 2013; Zhao et al., 2013; Zhao and Guan, 2016; Zhai et al., 2017; Shi et al., 2019) or use chance-constrained optimization (Zhang et al., 2017; Sundar et al., 2019; Vrakopoulou et al., 2013; Roald and Andersson, 2018).

Expanding these methods to allow for a flexible uncertainty range can sometimes be difficult. For example, Shao et al. (2017) expand the standard robust UC formulation to include flexible uncertainty sets, thus allowing the uncertainty range to be reduced through curtailment. However, this significantly increases the complexity of the formulation. On the other hand, Morales-España et al. (2018) show that under certain restrictions on the uncertainty set a robust UC with dispatchable wind power can be translated into an equivalent single-level MIP, thus simplifying the formulation. Another example is presented by Roald et al. (2016), where chance constraints are used for limiting the probability of having insufficient reserves to cover wind power fluctuations. When the wind power fluctuations are assumed to be normally distributed this allows for a tractable reformulation of the chance constraints using formulas for normally distributed variables. However, enforcing a strict upper bound on the wind power fluctuation, as required for curtailment, introduces the need to evaluate the chance constraints using numerical integration with Monte-Carlo sampling, thus considerably increasing the computational complexity of the formulation.

Methods for handling uncertainty in power system operation have an inherent disadvantage if they are not able to represent the VRE uncertainty in a simple manner while simultaneously allowing this uncertainty to be reduced by curtailment. For this reason formulations that rely on pre-determined, but adjustable, reserve requirements may be preferable. For example, (Morales-España et al. 2016) account for wind uncertainty by setting separate requirements for capacity and ramp reserves, based on the expected capacity range of wind power production and the expected hourly wind power ramp excursions. This allows curtailment to be handled in a more straightforward manner, by reducing the reserve requirements.

Regarding VRE support schemes, our examples highlight the importance of achieving better market integration of VRE so that they participate based on their true costs, as opposed to support schemes that give incentives for VRE to maximize its energy production without regard to its value to the system. It is widely acknowledged that energy-based support schemes create barriers to market integration of VRE (Huntington et al., 2017; Newbery et al., 2018; Hu et al., 2018). In Huntington et al. (2017) a capacity-based support mechanism is proposed, whereby a VRE producer receives compensation payments based on the market value of the production of a reference plant with similar characteristics: a lower market value gives higher compensation payments. Since this decouples the compensation payments from the VRE producer's own production, only market forces are left to dictate the operational decisions. Capacity-based support schemes such as this will also give incentives to VRE installations designed to maximize the system value of the produced electricity, rather than maximizing the energy output. Examples may be installing PV-panels in a way that their daily production profile is more aligned with the daily demand pattern (Huntington et al., 2017). Hu et al. (2018) also argue that capacity-based support schemes may be preferable for market integration, and suggest a range of other changes in market design such as nodal pricing and shorter market time intervals. Additionally, capacity-based support schemes have been found to be more effective in reducing technology costs than energy-based subsidies (Özdemir et al., 2019).

In some EU countries steps towards decreasing the negative market impact of energy-based support schemes have been taken, e.g., by removing energy subsidies for periods with negative prices for more than 6 consecutive hours (Höfling et al., 2015; RVO, 2021), and it would be possible to further restrict subsidies during periods with negative prices. However, due to the non-convexities in UC problems there may not always exist energy prices that give incentives for individual producers to follow the optimal generation schedule (Gribik et al., 2007; Eldridge et al., 2020). This means that even if no subsidies are given during hours with negative prices the resulting VRE curtailment may not be optimal from a system perspective.

For small scale generation there are also cost-related and technical barriers to achieving higher market integration. There has been worries that as support schemes for small scale VRE are phased out, this will lead to decomissioning of significant amounts of VRE, e.g., for small scale PV in Germany (Apunn and Wehrmann, 2019). This shows the challenge of designing support schemes that give enough support for small scale VRE installations to be viable, while at the same time not causing excessive integration costs. However, affordable control systems and aggregation are being more widely used to operate small scale VRE in a more coordinated and system-friendly manner (NREL, 2018).

Finally, we showed in Section 4 that applying regression analysis to estimate the impact of VRE on CO_2 emissions can give misleading results due to the dynamics of power systems, such as the binary nature of the commitment decisions and coupling between different time periods. For this reason studies such as Clancy et al. (2015) and Weigt et al. (2013) that use power system models to assess the impact on CO_2 emissions may be preferable over econometric models. However, it is not certain to which degree the findings here extend to more realistic test systems, and for future research it would be interesting to perform UC studies together with regression analysis for larger test systems to see if similar results are obtained.

6. Conclusion

There is a widespread belief that more variable renewable energy (VRE) is always better, at least in the sense that more VRE will reduce CO_2 emissions. This is reflected in the general literature and in many formulations for power system operation under VRE uncertainty, which do not consider VRE curtailment when optimizing the system. In real power systems many VRE support schemes give incentives for VRE to produce at negative prices, and our analysis of market data shows that there is wind power bidding below −100 EUR/MWh in both the Nordpool market area and in the Netherlands.

However, in this paper we demonstrate that it is a misconception that increasing VRE production always decreases CO_2 emissions. To this end, we identify the constraints in power system operation that can lead to situations when, paradoxically, curtailing VRE simultaneously reduces system costs and CO_2 emissions. The cases are illustrated using stylized examples based on realistic generator characteristics, using unit commitment (UC) and economic dispatch (ED) for optimal power system operation. Broadly defined these situations when VRE curtailment is beneficial can occur 1) due to network constraints which create the need for inefficient redispatch actions if VRE is not curtailed, 2) due to increased need for flexibility from the system in terms of unit cycling and increased ramp capabilities, and 3) due to reserve/security requirements.

Instead of seeing curtailment as a measure of last resort to preserve system security, VRE should always be dispatched through the market based on its operating costs, to achieve the most economical, efficient, and least polluting operation of the power system, thus maximizing the value of VRE to the system rather than its output.

Conflict of interest statement

The authors of this paper certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

CRediT authorship contribution statement

Germán Morales-España: Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing, Supervision. **Elis Nycander**: Software, Validation, Investigation, Writing - original draft, Writing - review &editing. **Jos Sijm**: Writing - review & editing, Project administration.

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Appendix A. Model formulations

This section provides the mathematical formulations for the examples in Section 3. The general form for the ED, UC, and stochastic UC formulations are given, and Table A.1 lists the constraints that are included for each example. For easy comparison Table A.2 lists which type of constraints are present in each formulation without referring to the equation numbers. Notice that for all formulations, the wind dispatch can either be optimized or wind can be forced to its maximum available output. All formulations here minimize system operation costs. However, it is straightforward to solve the same problem while minimizing the CO_2 emissions instead, which is done by replacing costs C_g^{MC}, C_g^{SU} with emissions E_g^{MC}, E_g^{SU} in the objective. For all examples, minimizing costs and CO_2 emissions give the same result.

Table A.1
Formulations used in examples.

Example		Units	Obj.	Constraints
1	Network	CCGT, CT	(A.1)	(A.2), (A.4)-(A.6)
2	Ramp	CCGT, CT	(A.1)	(A.2)-(A.5)
3	Startup	ST	(A.7)	(A.8)-(A.9), (A.11), (A.14)-(A.15)
4	Min uptime	CCGT, ST	(A.7)	(A.8)-(A.15)
5	Stochastic	CCGT, ST, CT	(A.18)	(A.19)-(A.25)
6	N-1 Security	CCGT, ST, CT	(A.7)	(A.8)-(A.17)

Table A.2
Type of constraints used in examples.

Example		Min. prod.	Ramping	Min. up/down times	Network	N-1 security
1	Network				x	
2	Ramp		x			
3	Startup	x				
4	Min Uptime	x	x	x		
5	Stochastic	x	x	x		
6	N-1 Security	x	x	x		x

A.1. Nomenclature

Sets:

B—network buses, indexed b

$\mathcal{G}$—conventional generator units, indexed g

$\mathcal{T}$—time periods, indexed t∈[1, …, T]

Parameters:

C_g^{MC}—marginal cost of unit g [$/MWh]

C_g^{SU}—startup cost of unit g [$]

D_t, D_{bt}—aggregate load/load at bus b for time t [MWh]

E_g^{MC}—marginal emissions of unit g [ton/MWh]

E_g^{SU}—startup emissions of unit g [ton]

$\overline{F}_l$—capacity of line l [MW]

N_s—number of wind scenarios

$\overline{P}_g, \underline{P}_g$— max / min production of unit g [MW]

RU_g, RD_g—up/down ramp capability of unit g [MW/h]

TU_g, TD_g—minup/down time for unit g [h]

W_t, W_{st}—available wind production for time t (and scenario s) [MWh]

Γ_{lb}—sensitivity (PTDF) of line l to injections at bus b [p.u.]

Variables:

p_{gt}, p_{gst}—production of unit g for time t (and scenario s) [MWh]

r_{gt} − spinning reserves held by unit g at time t [MW]

u_{gt} − binary commitment variable for unit g and time t

v_{gt}, z_{gt} − binary startup/shutdown variable for unit g and time t

w_t, w_{st} − wind production for time t (and scenario s) [MWh]

A.2. Economic Dispatch (ED)

The general ED problem is to minimize energy cost (A.1) subject to capacity constraints (A.2), ramp constraints (A.3), limits for wind power production (A.4), demand balance (A.5), and network constraints (A.6):

$$\min \sum_{t \in \mathcal{T}} \sum_{g \in \mathcal{G}} C_g^{MC} p_{gt} \quad \text{s.t.} \tag{A.1}$$

$$0 \le p_{gt} \le \overline{P}_g \quad \forall g, t \tag{A.2}$$

$$-RD_g \le p_{gt} - p_{g,t-1} \le RU_g \quad \forall g, t \tag{A.3}$$

$$0 \le w_t \le W_t \quad \forall t \tag{A.4}$$

$$\sum_{g \in \mathcal{G}} p_{gt} + w_t = \sum_{b \in \mathrm{B}} D_{bt} \quad \forall t \tag{A.5}$$

$$-\overline{F}_l \le \sum_{g \in \mathcal{G}} \Gamma_{l,b(g)} p_{gt} + \Gamma_{l,b(w)} w_t - \sum_{b \in \mathrm{B}} \Gamma_{lb} D_{bt} \le \overline{F}_l \quad \forall l, t \tag{A.6}$$

A.3. Unit Commitment (UC)

The general UC problem is

$$\min \sum_{t \in \mathcal{T}} \sum_{g \in \mathcal{G}} \left(C_g^{MC} p_{gt} + C_g^{SU} v_{gt} \right) \quad \text{s.t.} \tag{A.7}$$

$$\underline{P}_g u_{gt} \le p_{gt} \quad \forall g, t \tag{A.8}$$

$$p_{gt} + r_{gt} \le \overline{P}_g u_{gt} \quad \forall g, t \tag{A.9}$$

$$-RD_g \le p_{gt} - p_{g,t-1} \le RU_g \quad \forall g, t \tag{A.10}$$

$$u_{gt} - u_{g,t-1} = v_{gt} - z_{gt} \quad \forall g, t \tag{A.11}$$

$$\sum_{i=t-TU_g+1}^{t} v_{gi} \le u_{gt} \quad \forall g, t \in [TU_g, T] \tag{A.12}$$

$$\sum_{i=t-TD_g+1}^{t} z_{gi} \le 1 - u_{gt} \quad \forall g, t \in [TD_g, T] \tag{A.13}$$

$$0 \le w_t \le W_t \quad \forall t \tag{A.14}$$

$$\sum_{g \in \mathcal{G}} p_{gt} + w_t = D_t \quad \forall t \tag{A.15}$$

$$\sum_{h \in \mathcal{G} \setminus \{g\}} r_{ht} \ge p_{gt} \quad \forall g, t \tag{A.16}$$

$$\sum_{g \in \mathcal{G}} r_{gt} \ge w_t \quad \forall t \tag{A.17}$$

The cost function (A.7) contains energy production costs and startup costs (no-load costs are zero for all UC examples). The units are restricted by capacity constraints (A.8)-(A.9), ramp constraints (A.10), commitment logic (A.11), minimum up/down times (A.12)-(A.13), and wind power is subject to production limits (A.14). Finally, demand balance is enforced using (A.15), and the N-1 security requirement that the remaining online generators have enough reserves to cover the outage of a conventional unit or the wind farm is enforced by (A.16)-(A.17). Note that for formulations without constraints (A.16)-(A.17), the reserve variable r_{gt} must be removed from (A.9). For a more elaborated and efficient UC formulation for solving large-scale problems, see (Gentile and Morales-España, 2017).

A.4. Stochastic Unit Commitment

The stochastic formulation for Example 5 is given by

$$\min \sum_{t \in \mathcal{T}} \sum_{g \in \mathcal{G}} C_g^{SU} v_{gt} + \frac{1}{N_s} \sum_{s=1}^{N_s} \sum_{t \in \mathcal{T}} \sum_{g \in \mathcal{G}} C_g^{MC} p_{gst} \quad \text{s.t.} \tag{A.18}$$

$$\underline{P}_g u_{gt} \le p_{gst} \le \overline{P}_g u_{gt} \quad \forall g, s, t \tag{A.19}$$

$$-RD_g \le p_{gst} - p_{gs,t-1} \le RU_g \quad \forall g, s, t \tag{A.20}$$

$$u_{gt} - u_{g,t-1} = v_{gt} - z_{gt} \quad \forall g, t \tag{A.21}$$

$$\sum_{i=t-TU_g+1}^{t} v_{gi} \le u_{gt} \quad \forall g, t \in [TU_g, T] \tag{A.22}$$

$$\sum_{i=t-TD_g+1}^{t} z_{gi} \le 1 - u_{gt} \quad \forall g, t \in [TD_g, T] \tag{A.23}$$

$$0 \le w_{st} \le W_{st} \quad \forall s, t \tag{A.24}$$

$$\sum_{g \in \mathcal{G}} p_{gst} + w_{st} = D_t \quad \forall t \quad \forall s, t \tag{A.25}$$

where the objective function (A.18) is the sum of startup costs and the expected energy production costs, calculated as the average over the wind power scenarios. The commitment decisions u_{gt}, v_{gt}, z_{gt} are first stage decision variables and the energy dispatches p_{gst} and w_{st} are second stage decisions.

Appendix B. Data

Table B.3 shows the load and wind data used in the examples.

Table B.3
Load and wind data.

Example	2. Ramp	3. Startup	4. Min. Uptime	5. Reserves	6. N-1 Security
Hour			Load [MWh]		
1	160	180	300	250	300
2	160	180	300	250	300
3	380	180	410	250	300
4	380	180	410	250	300
5	–	–	410	250	300
6	–	–	410	250	300
7	–	–	300	250	300
8	–	–	300	250	300
Hour			Wind [MWh]		
1	100	100	100	100, 100	150
2	100	180	100	100, 100	150
3	100	180	100	100, 150	170
4	100	100	220	100, 180	170
5	–	–	220	100, 180	170
6	–	–	100	100, 180	170
7	–	–	100	100, 150	150
8	–	–	100	100, 100	150

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