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Publication date
2017

Document Version
Accepted author manuscript

Citation (APA)
Morales-España, G., & Hobbs, B. F. (2017). *Are Optimal Day-Ahead Markets Able to Face RES Uncertainty? Evaluating Perfect Stochastic Energy Planning Models*. 1-6. Erasmus Energy Forum 2017, Rotterdam , Netherlands.

Are Optimal Day-Ahead Markets Able to Face RES Uncertainty? Evaluating Perfect Stochastic Energy Planning Models*

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Abstract

Approximations made in day-ahead markets can result in suboptimal or even infeasible schedules for generating units and inaccurate predictions of actual costs and wind curtailment. Here we compare different optimal models of day-ahead markets based on unit commitment (UC) formulations, especially energy- vs. power-based UC; excluding or including startup and shutdown trajectories; and deterministic vs. "ideal" stochastic models to face wind uncertainty. The day-ahead hourly schedules are then evaluated against actual wind and load profiles using a (5-min) real-time dispatch model. We find that each simplification usually causes expected generation costs to increase by several percentage points, and results in significant understatement of expected wind curtailment and, in some cases, load interruptions.

1 Introduction

Power systems worldwide now face a sustained and significant growth of variable and uncertain renewable generation driven by concerns for the environment, energy security and rising fuel prices. To maintain the supply-demand balance, enough system flexibility must be scheduled in advance to compensate for possible variations in load and renewable output. The day-ahead Unit Commitment (UC) is the planning process that is commonly used to schedule this flexibility at minimum cost, while operating the system within secure technical limits (Hobbs et al., 2001).

In deterministic UC models, the required amount of flexibility from the system is defined by specifying a required amount of reserves. The key question is then to define the optimal amount of reserves to the net load uncertainty, which can be achieved by solving a stochastic UC that fully describes net load uncertainties (Morales-España, 2014).

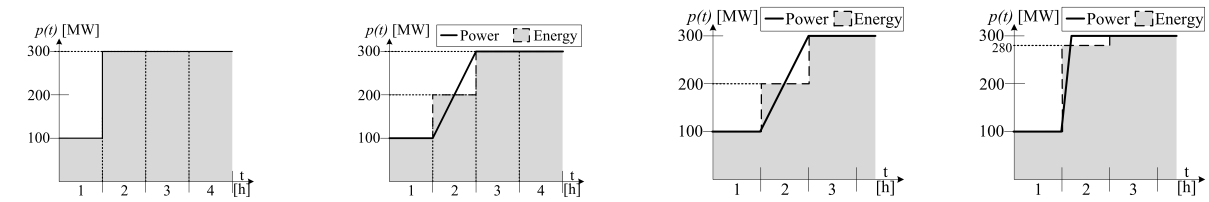
Many day-ahead markets are based on UC formulations to optimally guarantee a given level of flexibility for system operation, where the underlying assumption is that the UC generation schedule can always deliver what it apparently promises. However, conventional day-ahead UC formulations make coarse approximations of system ramp capabilities by using averaged energy levels within a large (usually 1 hour) scheduling interval and imposing ramp-constraints on these average hourly levels. Consequently, energy schedules may be infeasible (Guan et al., 2000; Yang et al., 2012; Morales-Espana et al., 2012). In addition, traditional UC models disregards the intrinsic units' startup (SU) and shutdown (SD) power trajectories. As a consequence, there may be a high amount of energy that is not allocated by the UC but which is nevertheless present in real time operations, thus affecting the total load balance. Although all these drawbacks suggest that traditional UC formulations may lead to unfeasible real-time operation and incorrectly characterize system flexibility, they are hidden within the UC formulations and hence are difficult to assess.

This paper reveals and quantifies the impact of the above theoretical drawbacks of traditional UC formulations, by following the day-ahead UC with a simulated real-time dispatch stage. For this purpose, a 5-min optimal dispatch is used to mimic actual real-time system operations. As shown in our numerical results, the real-time dispatch stage reveals that traditional UCs perform very different than expected and can even lead to infeasible real-time operation.

We show that stochastic energy-based UC is unable to manage real-time uncertainty, even if the stochastic UC considers the full range and correct probability distributions of the net load. To evaluate the performance of a "perfect" stochastic UC, the real-time (5-min) dispatch stage uses the same net load scenarios that are considered when solving the stochastic UC.

The remainder of this paper is organized as follows. Section 2 conceptually describes the drawbacks of energy-based approaches that distort the actual flexibility of the system, and summarizes an alternative, more accurate power-based UC model. Section 3 provides and discusses different case studies. Finally, conclusions are presented in Section 4.

*Work based on Morales-España et al. (2017)



(a) Energy-based schedule (b) Energy-based operation (c) Power-based schedule (d) Power-based operation

Fig. 1: Expected scheduling vs. Actual feasible real-time operation

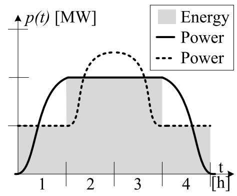


Fig. 2: Two power profiles with identical energy profile.

2 Inherent System Inflexibility Imposed by UC Formulations

2.1 Traditional Energy-based UC

Traditional UC formulations fail to deal with ramp capabilities appropriately. Inefficient ramp management arises from applying ramp-constraints to energy levels or (hourly) averaged generation levels. To illustrate this problem, consider the following scheduling example for one generating unit. This example assumes that the minimum and maximum generation outputs of the unit are 100 MW and 300 MW, respectively, with a maximum ramp rate of 200 MW/h. It is also assumed that the unit is committed all the time, i.e., the unit is always producing at least 100 MW. Fig. 1a shows a typical result that can be expected from an energy-based UC: if the unit produces 100 MWh for the first hour then the unit can deliver 300 MWh for the next hour. To produce an energy output of 100 MWh for the first hour, the unit must must have a constant power output of 100 MW for complete first hour (because the unit cannot produce below its minimum output when committed); similarly, the unit must have a constant power output of 300 MW during the complete second hour to produce 300 MWh. However, once the unit has been producing 100 MW for the first hour, the unit is just physically capable to reach its maximum output before the end of the second hour due to its limited ramp rate, as shown in Fig. 1b. Consequently, the solution obtained in Fig. 1a by the energy-based UC is not feasible. In fact, the unit requires an infinite ramping capability to be able to reproduce the energy schedule presented in Fig. 1a. More examples of this energy infeasibility problem can be found in Guan et al. (2000, 2009); Morales-Espana et al. (2012); Morales-España (2014).

In addition, the energy-based scheduling approach cannot guarantee that a given power demand profile can be supplied. To illustrate this problem consider the following example. Fig. 2 shows two power demand profiles that present the same energy profile. Notice that the two power profiles present distinctly different ramp requirements, even though the hourly energy requirements are identical. One energy profile has an infinite number of potential power profiles. Not all of the possible power profiles are necessarily feasible, even if the energy-based UC model shows the energy profile to be feasible. Thus, even though the energy-based UC could in theory provide a given energy profile, this approach cannot guarantee that the final resulting power profile can be supplied (Morales-Espana et al., 2014; Morales-España, 2014).

Another drawback is that conventional UC formulations assume that units start/end their production at their minimum output (Hobbs et al., 2001). That is, traditional UCs ignore the intrinsic SU and SD power trajectories of generating units which are inevitably present in the real-time operation. Consequently, there is energy that is not allocated by day-ahead scheduling approaches that will affect the total load balance during real-time operation. Considering these power trajectories in the scheduling stage can significantly change commitment decisions and also decrease operating costs (Morales-Espana et al., 2013b).

2.2 Power-based UC

To overcome the drawbacks of conventional energy-based UC formulations, the power-based UC formulation was proposed in Morales-Espana et al. (2014); Morales-España et al. (2015). The power-based model draws a clear distinction between power and energy, and it also takes into account the often neglected SU and SD power trajectories.

The power-based UC, however, assumes that power varies linearly from the beginning to the end of each hour. Let us consider a thermal unit that is required to increase its production from 100 MW to its maximum output 300 MW (see Fig. 1c). In practice, a very fast unit would operate at its maximum ramp and therefore reach its maximum output before the end of the hour (Fig. 1d). Nevertheless, if an hourly linear power profile is considered, the model assumes that the maximum generation will be attained only at the end of the hour (Fig. 1c), hence underestimating the ramp capabilities of fast units.

In short, the maximum flexibility of high ramping units will not be fully exploited in power-based UC. Therefore, although power-based UC ensure feasibility over energy-based UC, it may sacrifice some optimality. In the case of energy-based UC, however, the solution cannot even guarantee feasibility, because unit ramping capabilities are generally overestimated.

3 Numerical Results and Discussion

3.1 UC Formulations and Case Study

To evaluate the performance of different UC approaches, we use the modified IEEE 118-bus test system described in Morales-España (2014) for a time span of 24 hours. The system has 118 buses, 186 transmission lines, 91 loads, 64 thermal units, 10 of which are quick-start units, and three buses with wind production. Load is assumed to be known, so that forecast uncertainty is entirely in wind, represented by 20 scenarios (which, on average represent 24.4% of the energy demand).

Two different UC approaches are implemented, along several variations: the traditional energy-based UC and the power-based UC. The variations include with and without SU and SD power trajectories, as well as deterministic and stochastic versions. Thus, there are eight UC formulations[1] in total, two each (stochastic and deterministic) for each of the following cases:

- E-UC: traditional energy-based UC, excluding SU and SD trajectories.
- Es-UC: traditional energy-based UC, including SU and SD trajectories.
- P-UC: power-based UC, excluding SU and SD trajectories.
- Ps-UC: power-based UC, including SU and SD trajectories.

The deterministic E-UC is the commonly used UC approach, in which the energy demand is represented using energy levels (hourly-averaged generation) in a stepwise fashion over time. All constraints involving generation levels are applied to these energy levels. For this study, we use the UC formulation in Morales-Espana et al. (2013a) to represent E-UC. The SU and SD trajectories are included in Es-UC using the model in Morales-Espana et al. (2013b).

The power-based UC proposed in Morales-Espana et al. (2014); Morales-España et al. (2015) draws a clear distinction between power and energy. Demand and generation are modeled as hourly piecewise-linear functions representing their instantaneous power trajectories. The schedules are no longer an energy stepwise function, but a smoother piece-wise power function.

To observe that hidden inflexibilities imposed by the different UC formulations, we carry out an in-sample evaluation of the UC policies. That is, ideal stochastic UC formulations are mimicked by evaluating their performance in real-time (5 minute) dispatch using the same scenarios used in the scheduling stage. By doing this, we can show the problems that are related with the formulations rather than with the representation of the uncertainty itself, because in the in-sample evaluation, the stochastic UC formulations have perfect information about the uncertainty distributions.

[1] All UC formulations include demand balance and transmission constraints, and the units constraints: minimum up/down times, capacity and ramp limits. All optimizations were carried out using CPLEX 12.6.1 on an Intel-Xeon 3.7-GHz personal computer with 16 GB of RAM memory. The MIP problems are solved until they reach an optimality tolerance of 0.05%.

Table 1: Performance of Different Stochastic UC policies

Stochastic UC	Scheduling (hourly) TC [k$]	Scheduling (hourly) Curt [%]	Real-time Dispatch (5-min) TC [k$]	Real-time Dispatch (5-min) Curt [%]	Sch vs. Rtd* TC rtd/sch	Sch vs. Rtd* Curt rtd/sch
E-UC	733.19	1.33	719.78	8.06	0.983	6.044
Es-UC	713.06	2.53	720.88	5.11	1.009	2.018
P-UC	730.55	2.77	719.20	7.05	0.984	2.542
Ps-UC	708.45	4.98	709.83	5.38	1.002	1.08

* 'sch' denotes the scheduling stage, 'rtd' denotes the real-time dispatch stage

To assess the performance of the different network-constrained UCs, we differentiate between the *scheduling stage* and the *real-time dispatch* stage. In the *scheduling stage*, the 20 wind scenarios are used to solve the stochastic UC problems and to obtain a single hourly commitment schedule for the 54 slow-start units for a time span of 24 hours. In the *real-time dispatch stage*, the single slow-start unit commitment result from the scheduling stage is fixed, and the real-time (5-min) dispatch as well as commitment decisions for 10 quick-start units are optimized for each of the 20 individual wind scenarios using a network-constrained economic dispatch/quick-start commitment problem[2].

3.2 Nominal Case

The nominal case consists of the stochastic UC formulation using the 20 wind scenarios under the nominal assumptions about demand variability and wind bidding. Equal probabilities are assumed for all the scenarios. We assume that the wind units submit negative bids of -50 $/MWh. In this paper, negative bids are used to solve the UC scheduling and dispatch problems, but the resulting negative costs are excluded from the total costs (see TC in Table 1) to separate the effect of the quantity of curtailment from the total costs[3].

Table 1 shows the performance of the different stochastic UC formulations in terms of six metrics, two related to the day-ahead scheduling stage, two to real-time dispatch, and two comparing the day-ahead schedules with the actual dispatch. The two scheduling stage metrics: 1) Total (scenario-averaged) production costs (TC); and 2) percentage of potential wind production curtailed (Curt). The real-time dispatch metrics: 3) average total costs (TC); and 4) percentage of wind production curtailed (Curt). The final two metrics compare the outcomes predicted by the scheduling model vs. what was actually realized in the real-time dispatch stage (Sch vs Rtd): 5) the ratio of the TC obtained from the dispatch stage to that predicted in the scheduling stage (TC rtd/sch); and 6) the ratio of the dispatch stage (actual) curtailment to that predicted by the scheduling stage (Curt rtd/sch).

As shown in the last column of Table 1, all the curtailment ratios between the results of the real-time dispatch and the scheduling stage were higher than 1. The degree of unexpected curtailment in the dispatch stage indicates how well the UCs scheduled the extra resources (reserves) to provide flexibility to the system. A value greater than one means that the reserves that were scheduled to deal with wind are in the end used to deal with other inflexibilities of the system that were not considered in the UC scheduling stage (hidden inflexibility). A value lower than one means that the system had actually over-scheduled resources to deal with the planned level of uncertainty.

Based on this comparison of results, we can conclude the following:

1) Perfect Stochastic UCs: the stochastic formulations might be expected to present an optimal performance since they are being evaluated using the same in-sample scenarios. That is, the curtailment and total cost during in the real-time dispatch stage are expected to be the same as in the scheduling stage. However, these stochastic UCs are not able to face the perfectly known conditions (excluding within-hour power variability), leading to unplanned and inefficient use of resources to manage deterministic events that were ignored in the scheduling stage.

[2]This dispatch stage mimics the actual real-time system operation, which is is an approximation of the California ISO market design (FERC, 2012).

[3]Certain subsidies, such as feed-in-tariffs, motivate renewable energy generators to submit negative price offers. This practice may increase system operation costs and even emissions due to lessened flexibility Deng et al. (2015).

2) SU and SD power trajectories: UCs ignoring these trajectories presume that there is a level of flexibility that the units actually do not have. This inevitable leads to higher curtailment in real-time operation than anticipated in the scheduling stage because reserves that were supposed to be used to manage wind are used instead to accommodate the SU and SD trajectories.

3) Energy-based UC: once SU and SD trajectories are included in the energy-based UC (Es-UC), a curtailment ratio above 1 still occurs, indicating that there is some inflexibility that is hidden in the energy-based scheduling formulation. As discussed in Section 2, the traditional energy-based UC over-estimates the units' ramping capabilities and cannot guarantee that the commitment decisions can actually provide the resulting energy schedule, hence extra resources are needed in real-time operation to compensate this ramping over-estimation. This was reflected in additional quick-start units were started up or wind was curtailed, increasing costs.

4) Power-based UC: Ps-UC presents the best overall economic efficiency with the lowest actually realized value of the objective function (\$709.83). Ps-UC also results in the most accurate scheduling-stage estimate of wind curtailment in the scheduling compared to real-time dispatch (rtd/sch = 1.08). It is important to acknowledge that the curtailment ratio increases due to any intra-hour variation that could not be taken into account into the hourly UC model. However, this ratio could also decrease because the hourly Ps-UC underestimates ramp capabilities for faster ramping units (Section 2).

3.3 Stochastic vs. Deterministic UC

This section compares the real-time dispatch performance of deterministic[4] UCs with stochastic UCs, by using the actual 20 wind realizations in the dispatch stage.

In the nominal case, for a given UC, the stochastic formulation performs better during real-time operation than the deterministic formulation in terms of both costs. This is expected since the stochastic model optimizes the reserves considering all 20 possible wind scenarios. However, the following two extreme cases, in demand variability and wind bid, did not perform as expected and hence we discuss them in more detail as follows.

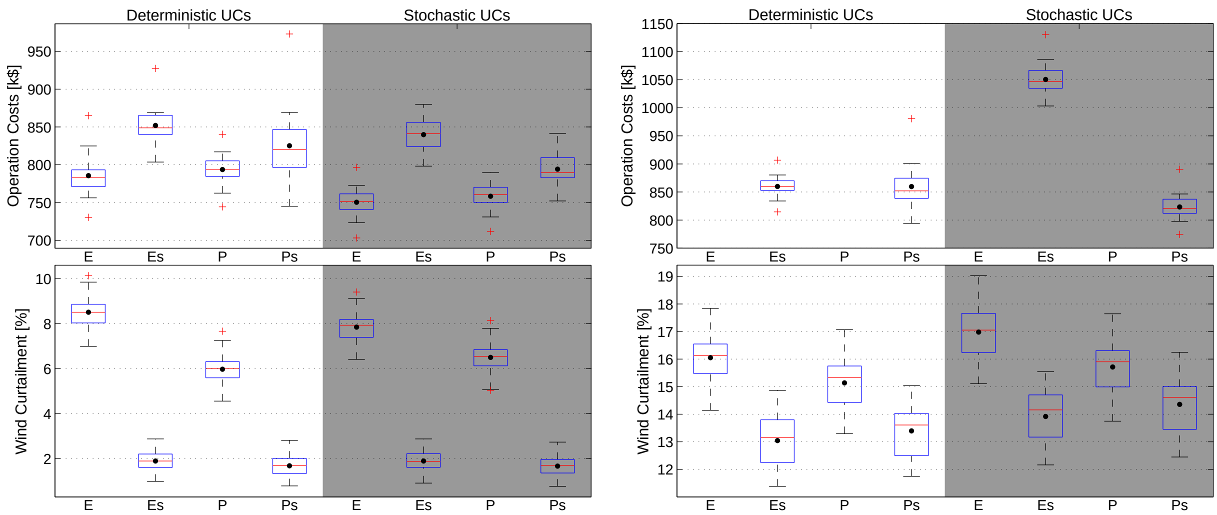
Fig. 3a compares the deterministic and stochastic UC models with a very low negative bid -500 \$/MWh which demands more flexibility from the system. One can observe that the deterministic Ps-UC formulation provides a better result than the stochastic Es-UC formulation. Although a stochastic approach outperforms a deterministic approach in general, the fact that the stochastic Es-UC formulation doesn't account for the hidden inflexibility discussed in Section 2, makes the Ps-UC deterministic approach to outperform the Es-UC stochastic approach. Not only the costs are lower for the Ps-UC deterministic approach, but the curtailment is also lower, which again is a result of a UC formulation that better represents the the flexibility of the power system.

Fig. 3b portrays the deterministic and stochastic UC results in the case of the highest demand variation (1.5 times the maximum-minimum load difference over the day). Noteworthy is that the deterministic Es-UC formulation provided better results than the stochastic Es-UC. The reason for this is that the Es-UC stochastic formulation had supply-demand balance infeasibilities that were not present in the Es-UC deterministic formulation. In the deterministic formulation a higher amount of reserves was imposed, whereas in the stochastic approach the level of reserves was lower because they are optimized in the UC stage. Because of the infeasibilities that were actually encountered in real time due to a shortage of reserves, the overall costs were higher for the Es-UC stochastic formulation. The deterministic formulation is usually less optimal in general, but in this particular case, thanks to having more reserves that provide flexibility, the deterministic formulation was able to cope with the higher demand variability, and in this way outperform the stochastic formulation. Similar phenomena were encountered for E and P.

4 Conclusions

We have shown how the performance of traditional optimal energy-based markets, based on UC formulations, could be more affected by inaccurate system representations than by wind uncertainty itself. This was demonstrated by comparing alternative formulations of the day-ahead

[4]Unlike the stochastic model, the deterministic UC uses the mean wind production and includes two hourly reserves constraints, upwards and downwards, which are defined as the mean wind production minus the minimum wind envelope, and the maximum wind envelope minus the nominal wind production, respectively.



(a) Wind bid -500 $/MWh (b) Variation of 1.5 the standard deviation demand

Fig. 3: Stochastic vs. Deterministic UC

hourly UC problem, and evaluating the quality and accuracy of their schedules through simulation of real-time (5-min) dispatch. The results demonstrate that even "ideal" energy-based stochastic UC formulation imposes a hidden system inflexibility, because the traditional energy-based UC formulation incorrectly represents ramp capabilities and also disregards the intrinsic units' startup and shutdown trajectories. In fact, it can be better to choose a deterministic approach that requires enough reserves than to use a stochastic approach that could present infeasibilities due to flaws in the formulation. Results also showed that a power-based deterministic formulation can outperform an energy-based stochastic formulation. In general, a power-based UC formulation presented lower actual cost and wind curtailments than energy-based UC, especially when more flexibility is demanded by the system, for instance due to high demand variability and larger negative wind bids.

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