Time-Adaptive Unit Commitment
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Abstract—The short-term operation of a power system is usually planned by solving a day-ahead unit commitment problem. Due to historical reasons, the commitment of the power generating units is decided over a time horizon typically consisting of the 24 hourly periods of a day. In this paper, we show that, as a result of the increasing penetration of intermittent renewable generation, this somewhat arbitrary and artificial division of time may prove to be significantly suboptimal and counterproductive. Instead, we propose a time-adaptive day-ahead unit commitment formulation that better captures the net-demand variability throughout the day. The proposed formulation provides the commitment and dispatch of thermal generating units over a set of 24 time periods, but with different duration. To do that, we use a clustering procedure to select the duration of those adaptive time periods taking into account the renewable generation and demand forecasts. Numerical results show that, without increasing the computational burden, the proposed time-adaptive unit commitment allows for a more efficient use of the system flexibility, which translates into a lower operating cost and a higher penetration of renewable production than those achieved by a conventional hourly unit commitment problem.

Index Terms—Clustering techniques, economic dispatch, renewable generation, unit commitment.

NOMENCLATURE
The main symbols used throughout this paper are explained next. Others are defined as required.

A. Indexes and sets

| Symbol | Description |
|--------|-------------|
| $g$    | Conventional generating unit index. |
| $t$    | Time interval index. |

B. Parameters

| Symbol | Description |
|--------|-------------|
| $C_{LS}$ | Load shedding cost (€/MWh). |
| $C_{Mg}$ | Marginal generation cost of unit $g$ (€/MWh). |
| $C_{SUg}$ | Start-up cost of unit $g$ (€). |
| $d_t$ | Duration of time interval $t$ (h). |
| $DT_g$ (UT$_g$) | Minimum down (up) time of unit $g$ (h). |
| $DT_g^0$ (UT$_g^0$) | Number of hours unit $g$ has been offline (online) prior to the first period (h). |

| Symbol | Description |
|--------|-------------|
| $DT_g^l$ (UT$_g^l$) | Number of hours unit $g$ must be initially offline (online) due to its minimum down (up) time constraint (h). |
| $DT_g$ (UT$_g$) | Dynamic minimum down (up) time of unit $g$ at time interval $t$ (# time periods). |
| $DT_g^E$ (UT$_g^E$) | Minimum down (up) time of unit $g$ at the end of the time horizon (# time periods). |
| $DT_g^I$ (UT$_g^I$) | Number of time periods unit $g$ must be initially offline (online) due to its minimum down (up) time constraint. |

| Symbol | Description |
|--------|-------------|
| $N_t$ | Number of time periods. |
| $P_t^D$ | Demand at time $t$ (MW). |
| $P_g^G$ (L$_g^G$) | Maximum (minimum) production of thermal unit $g$ (MW). |
| $P_g^S$ (P$_g^W$) | Installed capacity of solar (wind) generation (MW). |
| $RD_g$ (RU$_g$) | Ramp-down (Ramp-up) limit of unit $g$ (MW/h). |
| $SD_g$ (SU$_g$) | Shutdown (Start-up) ramp limit of unit $g$ (MW/h). |
| $U_g^0$ | Initial commitment state of unit $g$ (1 if online, and 0 otherwise). |
| $\alpha^S$ ($\alpha^W$) | Percentage of yearly demand covered by solar (wind) generation (%). |
| $\rho_g^S$ ($\rho_g^W$) | Capacity factor of solar (wind) generation at time interval $t$ (p.u.). |

C. Variables

| Symbol | Description |
|--------|-------------|
| $p_{gt}^D$ | Power output of unit $g$ at time interval $t$ (MW). |
| $p_{gt}^W$ (P$_g^W$) | Power from solar (wind) generation at time interval $t$ (MW). |
| $s_{gt}^I$ | Satisfied demand in time interval $t$ (MW). |
| $s_{gt}^U$ | Start-up cost of unit $g$ at time interval $t$ (€). |
| $u_{gt}$ | Binary variable that is equal to 1 if thermal unit $g$ is online at time interval $t$ and 0 otherwise. |

I. INTRODUCTION

T HE objective of the unit commitment (UC) problem is to determine the on/off status and production level of all generating units to satisfy the electricity demand at the minimum operating cost taking into account the system-wide technical constraints [1]. Although initially designed to centrally operate power systems, the UC problem is also widely used in deregulated environments to obtain the accepted bids and offers that maximize the social welfare while complying with technical constraints [2]. The UC problem is commonly formulated as a mixed-integer quadratic optimization problem and a review of the main methods to solve it can be found in [3], [4]. Solving a UC problem is computationally expensive...
because of its combinatorial nature and therefore, some authors have proposed methods to reduce its computational burden [5, 6]. Due to the high penetration of fluctuating renewable energy, day-ahead decisions have to be made facing a significant level of uncertainty, which has led to stochastic formulations of the UC problem [7].

Besides the more important role of uncertainty in the operation of power systems, the integration of renewable generation requires further modifications of the traditional unit commitment and economic dispatch tools [8]. One of the potential changes currently under debate relates to the time resolution chosen to determine the day-ahead commitment and dispatch quantities of thermal generating units. In 2012, the Federal Energy Regulatory Commission (FERC) stated that “hourly transmission scheduling protocols (...) are insufficient to provide system operators with the flexibility to manage their system effectively and efficiently” in the FERC Order 764 [9]. For this reason, the FERC proposed 15-minute schedules.

Following this line of argument, the authors in [10] investigate the impact of time resolution on the performance of the UC problem. They found out that 15-minute schedules lead to substantial savings through more efficient commitment and dispatch decisions at the expense of significantly increasing the computational needs. Similarly, reference [11] solves the UC problem for time resolutions of 5, 15, 30 and 60 min. They concluded that, in spite of the increase in computational times, higher time resolutions show benefits over traditional hourly simulation in power systems with relatively few flexible resources. The authors in [12] also analyze the effects of different time resolutions such as 60, 30, 15, 10 and 5 min on UC results. Their conclusion was that UC should be implemented in a higher time resolution to efficiently overcome the intra-hour variations of renewable generation. The UC results presented in [13] show that the use of hourly intervals to model the production of thermal units is an approximation leading to costly operational decisions. Alternatively, the authors of [14], [15] propose a unified UC and economic dispatch modeling tool that considers a finer time resolution during the first hours of the scheduling horizon and a coarser time resolution during the last ones. Their approach was proven to provide system operators with the flexibility to manage their system effectively and efficiently.” in the FERC Order 764 [9]. For this reason, the FERC proposed 15-minute schedules.

In short, existing works on this topic concluded that using finer time resolutions lead to operating cost savings compared to the results from the conventional hourly UC problem (CH-UC). However, these savings involve a significant increase in the computational burden. Note that increasing the number of time periods leads to an exponential raise of the computational time required to solve the UC problem to optimality. In fact, as stated in [17], “ISOs cannot currently solve their commitment problems to complete optimality within the allotted timeframe.” Therefore, although existing works have demonstrated the benefits of finer time resolutions to solve the UC problem, its implementation in current power systems is still unrealistic due to computational limitations.

In order to overcome this drawback, this paper proposes a time-adaptive day-ahead UC formulation that makes a more efficient use of the system flexibility without increasing its computational burden. To illustrate the key idea of our proposal, Fig. 1 represents the net demand of CAISO on April 22nd, 2018 with a time resolution of 5 minutes. The upper and lower plot correspond to the time aggregation of CH-UC and TA-UC, respectively.

![Fig. 1. Time aggregation for the net demand in the CAISO on April 22nd, 2018 with a time resolution of 5 minutes. The upper and lower plot correspond to the time aggregation of CH-UC and TA-UC, respectively.](image)
and consequently, reduce the total operating costs.

The contributions of this paper are thus threefold:

- The use of a hierarchical clustering algorithm to determine the duration of the 24 time intervals that better approximate the time-dependent parameters involved in the unit commitment problem.

- A novel formulation of a time-adaptive unit commitment problem that determines the commitment and dispatch of thermal generating units for time periods of different duration by using mixed-integer linear programming. Technical constraints of thermal generators such as ramping limits as well as minimum up and down times are adapted to take into account the varying duration of time intervals throughout the scheduling horizon.

- The comparison between the proposed approach and the conventional unit commitment in terms of the total operating costs and the share of renewable production.

The rest of this paper is organized as follows. The clustering technique used to determine the duration of time periods is explained in Section II while the proposed TA-UC problem is formulated in Section III. Section IV presents the methodology used to compare the proposed approach with the conventional one. The results of an illustrative example and a more realistic case study are provided in Sections V and VI, respectively. Finally, conclusions are duly drawn in Section VII.

II. TIME-PERIOD AGGREGATION

The procedure to determine the duration of time periods for the proposed TA-UC problem is based on clustering techniques [19]. In particular, we use hierarchical agglomerative clustering since its outcome is independent of the initialization of the algorithm and additional conditions on how the clusters are formed can be readily incorporated. In this paper we use an agglomerative hierarchical clustering based on Ward’s method [20]. This method recursively merges the two clusters that minimally increase the within-cluster variance.

The methodology used in this paper and described below is inspired by the one proposed in [21]. Let \( N \) be the total number of low-resolution time periods into which the user desires to divide the 24-hour scheduling horizon. Let \( x_i \) be a vector containing the normalized values of all time-dependent parameters at time point \( i \) (with \( i \) running from 1 to \( N' > N \)). For instance, \( x_i \) may have just one element corresponding to the aggregated net demand in the simplest case. The duration of the \( N' \) time periods is determined as follows:

1) Set the initial number of clusters \( n \) to the total number of high-resolution time periods \( N' \). That is, in this step, each data point \( x_i \) constitutes a cluster and \( n = N' \).

2) Determine the centroid \( \bar{x}_I \) of each cluster \( I \) as

\[
\bar{x}_I = \frac{1}{|I|} \sum_{i \in I} x_i
\] (1)

3) Compute the dissimilarity between each pair of adjacent clusters \( I, J \) according to Ward’s method using

\[
D(I, J) = \frac{2|I| |J|}{|I| + |J|} ||\bar{x}_I - \bar{x}_J||^2
\] (2)

4) Merge the two closest adjacent clusters \( (I', J') \) according to the dissimilarity matrix, i.e., \( (I', J') \in \text{argmin} \{ D(I, J) \} \) subject to \( J' \in A(I) \), where \( A(I) \) is the set of clusters adjacent to cluster \( I \). Two clusters \( I \) and \( J \) are said to be adjacent if \( I \) contains a high-resolution time period that is consecutive to a high-resolution time period in \( J \), or vice versa.

5) Update \( n \leftarrow n - 1 \).

6) If \( n = N' \), go to step 7). Otherwise go to step 2).

7) Determine the value of the parameters (e.g., the net demand) for each low-resolution time-period as its cluster’s centroid \( \bar{x}_I \).

8) The number of high-resolution time periods belonging to each final cluster determines the duration of each low-resolution time period, which is denoted by \( d_t \).

III. TIME-ADAPTIVE UNIT COMMITMENT

In this section we present the formulation of the proposed day-ahead TA-UC problem. For the sake of simplicity, this problem is formulated as a deterministic single-bus model. In other words, demand levels and renewable capacity factors are forecasted values and network constraints are ignored. Based on the model in [5], the proposed time-adaptive unit commitment problem is formulated as the following mixed-integer linear program:

\[
\min_{\beta} \sum_i d_t \left( \sum_g (s^{U}_{gt} + C_{gt}^{M} p^{G}_{gt}) + C_{gt}^{LS} (p^{D}_{t} - p^{G}_{t}) \right)
\] (3)

subject to:

\[
\sum_g p^{G}_{gt} + p^{W}_{t} + p^{S}_{t} = p^{D}_{t}, \quad \forall t
\] (4)

\[
0 \leq p^{D}_{t} \leq T^{D}_{t}, \quad \forall t
\] (5)

\[
0 \leq p^{W}_{t} \leq T^{W}_{t}, \quad \forall t
\] (6)

\[
0 \leq p^{S}_{t} \leq T^{S}_{t}, \quad \forall t
\] (7)

\[
u_{gt} - p^{G}_{gt} \leq p^{G}_{gt} - u_{gt} T^{G}_{g}, \quad \forall g, \forall t
\] (8)

\[
u^{U}_{gt} \geq C_{gt}^{SU} (u_{gt} - u_{gt-1}), \quad \forall g, \forall t
\] (9)

\[
u^{S}_{gt} \geq 0, \quad \forall g, \forall t
\] (10)

\[
u^{G}_{gt} - p^{G}_{gt-1} \leq R U_{g} u_{gt-1} + S U_{g} (u_{gt} - u_{gt-1}) + \bar{T}_{g} (1 - u_{gt}), \quad \forall g, \forall t
\] (11)

\[
u^{G}_{gt-1} - p^{G}_{gt} \leq R D_{g} u_{gt} + S D_{g} (u_{gt-1} - u_{gt}) + \bar{T}_{g} (1 - u_{gt-1}), \quad \forall g, \forall t
\] (12)

\[
u^{G}_{t} \leq T^{G}_{g} u_{gt} + S D_{g} (u_{gt} - u_{gt-1}), \quad \forall g, \forall t < N_{T}
\] (13)

\[
\sum_{t=1}^{t+\bar{T}_{g} - 1} (1 - u_{gt}) = 0, \quad \forall g
\] (14)

\[
\sum_{t=t}^{t+\bar{T}_{g} - 1} u_{gt} \geq \bar{T}_{g} (u_{gt} - u_{gt-1}), \quad \forall g, \forall t < N_{T}
\] (15)
∀g, ∀t = N_T − \overline{UT}_g^E + 2 \ldots N_T \quad (16)

\sum_{t=1}^{t+\overline{DT}_{gt}-1} (1 - u_{gt}) \geq \overline{DT}_{gt} (u_{gt-1} - u_{gt}), \quad ∀g \quad (17)

∀g, ∀t = \overline{UT}_g^I + 1 \ldots N_T - \overline{DT}_g^E + 1 \quad (18)

\sum_{\tau=t}^{N_T} (1 - u_{g\tau} - (u_{g\tau-1} - u_{g\tau})) \geq 0,

∀g, ∀t = N_T - \overline{DT}_g^E + 2 \ldots N_T \quad (19)

u_{gt} \in \{0, 1\}, ∀g, ∀t, \quad (20)

where Ξ is the set of dispatch decisions (p^G, p^W, p^D) and commitment decisions (u^G, s^G).

The objective function (3) comprises three terms, namely the production and start-up costs of thermal units as well as the costs due to load shedding. Constraints (4)–(8) set bounds on satisfied demand, wind power production, and thermal power production, respectively. Start-up costs are modeled by equations (9) and (10). Constraints (11)–(13) enforce the ramping rates of thermal units as described in [5], where the ramping rates in MW are given as $\frac{d_t}{dt} = \max\{P^G, X_d\}$ with symbol $X = \{RU, RD, SU, SD\}$. Note that $d_t = 0.5(d_{t-1} + d_t)$, i.e., power is assumed to ramp up or down from the middle point of intervals $t - 1$ and $t$. We also assume that ramp rates of thermal units cannot be greater than their respective capacities. Constraints (14)–(16) and (17)–(19) correspond to the minimum up-time and down-time constraints of thermal units, in that order. These constraints allow for predefined time intervals of different duration, by computing parameters $\overline{UT}_g^I$, $\overline{UT}_g^E$, and $\overline{UT}_{gt}$ ex-ante as follows:

\[\overline{UT}_g^I = \arg\min_{\omega=1,2,\ldots} \sum_{\tau=1}^{\omega} d_{\tau} \geq UT_g^I, \quad ∀g\] \quad (21)

\[\overline{UT}_g^E = \arg\min_{\omega=1,2,\ldots} \sum_{\tau=\omega+1}^{N_T} d_{\tau} \geq UT_g^E, \quad ∀g\] \quad (22)

\[\overline{UT}_{gt} = \arg\min_{\omega=1,2,\ldots} \sum_{\tau=t}^{t+\omega-1} d_{\tau} \geq UT_g^T, \quad ∀g, ∀t\] \quad (23)

where $UT_g^I = \min\{N_T, (UT_g - UT_g^0) U_g^0\}$. Analogously, the parameters associated with the minimum down times are computed in a similar fashion. Finally, the integrality of binary variables is imposed by constraints (20).

Note that if $d_t = 1 \forall t$, then $\overline{UT}_g^E = UT_g^E$, $\overline{DT}_g^E = DT_g^E$, $\overline{UT}_g^I = UT_g^I$, $\overline{DT}_g^I = DT_g^I$, $\overline{UT}_{gt} = UT_{gt}$, $\overline{DT}_{gt} = DT_{gt}$. Optimization model (3)–(20) becomes the CH-UC in [5]. Conversely, if the time period duration $d_t$ is determined following the algorithm in Section III, model (3)–(20) becomes the proposed TA-UC.

IV. COMPARISON METHODOLOGY

In this section we present the procedure to compare CH-UC and TA-UC. First, it is worth clarifying that thermal generating units are divided into three main groups according to their flexibility: base-load units, medium-load units and peak-load units. This implies that the commitment and dispatch of the base units and the commitment of the medium units have to be necessarily decided one day in advance and cannot be modified in the real-time operation of the system. On the other hand, the dispatch of the medium units and the commitment and dispatch of the peak units can adapt to the real-time net-demand. That said, the total operating cost for each methodology is computed as follows:

1) Forecast values for time-dependent parameters such as demand level and renewable capacity factors are provided in a high-resolution time scale (5 or 10 min).

2) Original data are approximated using 24 low-resolution time periods whose duration depends on each approach:
   a) CH-UC: the duration of all low-resolution time periods is equal to 1 hour.
   b) TA-UC: the duration of the low-resolution time periods is determined as explained in Section III.

3) Model (3)–(20) is solved for the low-resolution time series computed as described in step 2). This problem provides the day-ahead commitment and dispatch of base-load units and the commitment and dispatch of medium-load units.

4) Model (3)–(20) is solved again considering the original high-resolution time data and with the commitment and dispatch of base-load units and the commitment of medium-load units fixed to those obtained in step 3). This way, we are able to simulate the real-time operation of the system and the performance of the day-ahead decisions given by each methodology.

Let us denote the daily operating cost obtained in step 4) for CH-UC and TA-UC as $C^{CH}$ and $C^{TA}$, respectively. We evaluate the performance of the proposed approach by computing the relative difference between $C^{CH}$ and $C^{TA}$ as:

\[\Delta C(\%) = 100 \cdot \frac{C^{CH} - C^{TA}}{C^{CH}}\] \quad (24)

In order to draw conclusions about the proposed methodology, the daily cost difference $\Delta C$ must be computed for several consecutive days. To this end, the unit commitment model (3)–(20) is run in a rolling horizon with an 8-hour look-ahead window. The dispatch and commitment decisions in day $D$ are obtained by running the model in day $D$ plus a look-ahead window of length equal to 8 time intervals, which corresponds to the next day $D + 1$. The initial conditions are taken from the previous high-resolution simulation at the end of the time span from day $D - 1$. Finally, it is worth mentioning that the two approaches compared in this paper involve computational burdens of the same order of magnitude since both include the same number of constraints and continuous and binary variables.
V. ILLUSTRATIVE EXAMPLE

This section illustrates the performance of the proposed TA-UC by using a stylized example of six generating units, whose data is collated in Table I. For the sake of simplicity, minimum up and down times and ramp limits are neglected.

The time horizon of this illustrative example spans six time periods of 30 minutes each. Table I provides the demand, the solar power production as well as the net demand for each time period. Observe that the demand and the solar production increases and decreases in the last two time periods, respectively. The load shedding cost is set to €100/MWh.

To determine the commitment of units in a conventional fashion, the 30-minute time periods are merged two by two in order to determine the hourly day-ahead commitment and dispatch of each unit, provided in the upper part of Table III. The real-time generation levels of each generating technology, the load shedding and the solar spillage for each 30-min time period of the optimization horizon are shown in the lower part of Table III. Although the net demand of these two time periods are the same under this approach. This involves some solar spillage in t5, the start-up of the expensive peak unit and some load shedding in t6. The total operating cost for this conventional unit commitment plan is 18500€.

The TA-UC proposed in this paper also considers three time periods to determine the day-ahead commitment and dispatch of generating units. However, the time period aggregation is quite different. Since the first four 30-minute time periods have the same net demand, they are merged into a 2-hour time period, as illustrated in the upper part of Table IV. In this way, the day-ahead decisions adapt better to the net demand changes happening in t5 and t6 and load shedding and solar spillage are no longer required in the real-time operation. Under this approach, the total cost amounts to 11500€, then involving a 38% cost reduction with respect to the CH-UC.

VI. CASE STUDY

The proposed methodology is tested using a more realistic case study based on the Spanish power system. The Spanish electricity demand (after subtracting the hydro power production) during the year 2017 in a 10-minute time resolution is scaled down a factor of 10 in order to keep the computational burden of the UC problems within reasonable limits. The capacity factors of solar and wind power production are also taken from the Spanish system during the year 2017 in a 10-minute resolution. These data are publicly available in [22]. The installed capacity of wind and solar power generation are determined by [25] so that the share of demand covered by these technologies amounts to αS and αW, respectively.

\[
\mathcal{T}^S = \alpha_S \sum_t \frac{T^D_t}{\rho_t^S} \quad \mathcal{T}^W = \alpha_W \sum_t \frac{T^D_t}{\rho_t^W}
\]  

The generation portfolio is composed of 3 base-load units, 4 medium-load units, and 6 peak-load units, whose technical and economic data are provided in Table V. These parameters have been chosen according to [23] and the references therein. As observed, base-load units are cheap albeit inflexible, while peak-load power plants are flexible albeit expensive units. Note that the ramp rates, minimum up and down times, and marginal costs of units of the same type are slightly different in order to represent the variety of generating technologies. In all cases, higher flexibility implies higher marginal costs. Moreover, we assume that the minimum power output of peak-load units is 0 and their minimum up and down times are disregarded. Finally, the cost of load shedding is set to €10000/MWh.

The proposed TA-UC and conventional CH-UC models have been implemented on a Linux-based server with one CPU.

| Technology | \( P_{DG}^t \) (MW) | \( P_{CH}^M \) (MW) | \( C^M_g \) (€/MWh) | # units |
|------------|---------------------|---------------------|---------------------|--------|
| Base       | 150                 | 200                 | 10                  | 4      |
| Medium     | 50                  | 100                 | 30                  | 1      |
| Peak       | 0                   | 50                  | 50                  | 1      |

| Time period | \( t \) | \( t + 1 \) | \( t + 2 \) | \( t + 3 \) | \( t + 4 \) | \( t + 5 \) | \( t + 6 \) |
|-------------|--------|--------|--------|--------|--------|--------|--------|
| Duration (h) | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    | 0.5    |
| Demand (MW)  | 500    | 500    | 500    | 500    | 650    | 850    |
| Solar (MW)   | 300    | 300    | 300    | 300    | 200    | 0      |
| Net demand (MW) | 200    | 200    | 200    | 200    | 450    | 850    |

| Technology | \( P_{DG}^t \) (MW) | \( P_{CH}^M \) (MW) | \( C^M_g \) (€/MWh) | # units |
|------------|---------------------|---------------------|---------------------|--------|
| Base       | 150                 | 200                 | 10                  | 4      |
| Medium     | 50                  | 100                 | 30                  | 1      |
| Peak       | 0                   | 50                  | 50                  | 1      |

| Time period | \( t \) | \( t + 1 \) | \( t + 2 \) | \( t + 3 \) | \( t + 4 \) | \( t + 5 \) | \( t + 6 \) |
|-------------|--------|--------|--------|--------|--------|--------|--------|
| Net demand (MW) | 200    | 200    | 200    | 200    | 450    | 850    |
| Base        | 200    | 200    | 200    | 200    | 400    | 800    |
| Medium      | 0      | 0      | 0      | 0      | 50     | 50     |
| Peak        | 0      | 0      | 0      | 0      | 0      | 0      |
| Load shed   | 0      | 0      | 0      | 0      | 0      | 0      |
| Solar spillage (MW) | 0      | 0      | 0      | 0      | 0      | 0      |

| Time period | \( t \) | \( t + 1 \) | \( t + 2 \) | \( t + 3 \) | \( t + 4 \) | \( t + 5 \) | \( t + 6 \) |
|-------------|--------|--------|--------|--------|--------|--------|--------|
| Net demand (MW) | 200    | 200    | 200    | 200    | 450    | 850    |
| Base        | 200    | 200    | 200    | 200    | 400    | 800    |
| Medium      | 0      | 0      | 0      | 0      | 50     | 50     |
| Peak        | 0      | 0      | 0      | 0      | 0      | 0      |
| Load shed   | 0      | 0      | 0      | 0      | 0      | 0      |
| Solar spillage (MW) | 0      | 0      | 0      | 0      | 0      | 0      |
clocking at 2.6 GHz and 20 GB of RAM using CPLEX 12.6.3 [24] under Pyomo 5.2 [25]. Optimality gap is set to 0%.

For the sake of illustration, first we present the day-ahead schedule provided by each UC formulation for two typical days of 2017, namely March 19th and December 26th. The yearly penetration of wind and solar generation is 20% and 20%, respectively. March 19th is thus a representative day with abrupt intra-day net demand variations, which gives rise to the so-called “duck curve”, whereas December 26th is characterized by smooth intra-day net demand variations.

Fig. 2 plots the day-ahead dispatch of base- and medium-load units along with the real-time net demand on March 19th, 2017. The upper subplot corresponds to the results from CH-UC and the lower subplot to the ones from TA-UC. If the day-ahead dispatch of base- and medium-load units exceeds the net demand, then wind or solar spillage will occur in real-time operation. Conversely, if the net demand is higher than the day-ahead dispatch of base- and medium-load units, we remove January 1st and December 31st to neglect the impact of boundary conditions. Under these circumstances, the proposed TA-UC model without significantly increasing the computational burden. The average time to solve the day-ahead CH-UC and TA-UC are 5 and 7 seconds, respectively. The proposed TA-UC achieves higher shares of solar and base-load generation (cheap units) and lower shares of medium- and peak-load generation (expensive units).

Fig. 3 plots the same results for December 26th, 2017, which is a day with a particularly high wind production but barely none from solar generating units. For this reason, the intra-day net demand variations are much smoother and the day-ahead dispatch of the TA-UC (lower subplot) approximates the net demand very similarly to the CH-UC (upper subplot).

In fact, the real-time operating cost for TA-UC and CH-UC is thus a representative day with abrupt intra-day net demand variations, which gives rise to the so-called “duck curve”, whereas December 26th is characterized by smooth intra-day net demand variations.

We can observe that the net demand of Fig. 2 has two flat peaks (from 0:00 to 8:00 and from 20:00 to 23:59), a flat valley (from 11:00 to 17:00), and very steep net demand variations between the peaks and the valley (from 8:00 to 11:00 and from 17:00 to 20:00). This net demand profile is caused by a high solar production and a low wind penetration. The proposed model TA-UC takes advantage of that and chooses very long time periods during the peaks and the valley, but shorter time periods in the transitions, as can be seen in the lower subplot.

Comparing the two subplots of Fig. 2, it can be observed that the proposed TA-UC approximates the net demand much better than the conventional approach, which translates into a lower real-time operating cost. In fact, the real-time cost for TA-UC and CH-UC is €765366 and €783643, respectively. The relative cost saving for this day amounts to 2.33%.

Table VII provides the daily shares of the different production types on March 19th, 2017. It can be noticed that the TA-UC achieves higher shares of solar and base-load generation (cheap units) and lower shares of medium- and peak-load generation (expensive units).

Fig. 2. Day-ahead dispatch and real-time net demand for the CH-UC (upper plot) and the TA-UC (lower plot) on March 19th, 2017.

Table VI

| Model  | Wind (%) | Solar (%) | Base (%) | Medium (%) | Peak (%) |
|--------|----------|-----------|----------|------------|---------|
| CH-UC  | 9.52     | 32.48     | 45.26    | 12.36      | 0.38    |
| TA-UC  | 9.47     | 32.87     | 45.53    | 12.06      | 0.07    |

Table VII

| Model  | Wind (%) | Solar (%) | Base (%) | Medium (%) | Peak (%) |
|--------|----------|-----------|----------|------------|---------|
| CH-UC  | 38.35    | 3.30      | 44.99    | 13.35      | 0.00    |
| TA-UC  | 38.37    | 3.30      | 44.96    | 13.36      | 0.00    |
If we compare cases with the same renewable penetration that are poorly managed by the conventional CH-UC. Finally, since renewable generation creates steep net demand variations, this leads to higher yearly cost savings. This is to be expected because solar generation has abrupt changes around sunrise and sunset, thus giving rise to a net demand curve with very steep variations, commonly known as the “duck curve”. As evidenced throughout this case study, the proposed TA-UC model outperforms the conventional CH-UC approach in the presence of sudden net demand variations.

As shown in the first part of this analysis, the benefits of the proposed model depend on both the penetration level and the type of renewable generation. To investigate this aspect further, Table IX includes simulation results for the whole year 2017 under different penetration levels of wind and solar power production. Results in rows 2–6 are computed considering the same penetration level for wind and solar, while those in rows 7–11 and 12–16 refer to cases with wind and solar production only, respectively. This table shows the yearly cost savings achieved by the TA-UC model compared to the CH-UC, and the number of days for which the TA-UC provides lower, the same, or higher operating costs than the CH-UC, denoted as # TA<CH, # TA=CH, and # TA>CH.

The main conclusion that can be derived from Table IX is that the proposed model achieves significant yearly cost savings compared to the conventional approach in all cases without increasing the computational burden. Such cost savings range from 0.01% to 2.56% for the analyzed cases. By looking at any group of five rows of Table IX we can observe that an increase in the renewable penetration level leads to higher yearly costs savings. This is to be expected since renewable generation creates steep net demand variations that are poorly managed by the conventional CH-UC. Finally, if we compare cases with the same renewable penetration level but differently split between wind and solar, it can be concluded that the higher the renewable production coming from solar power plants, the larger the cost savings. This is so because solar generation has abrupt changes around sunrise and sunset, thus giving rise to a net demand curve with very steep variations, commonly known as the “duck curve”. As evidenced throughout this case study, the proposed TA-UC model outperforms the conventional CH-UC approach in the presence of sudden net demand variations.

Another important factor that may affect the performance of the proposed method is the flexibility of the thermal generation portfolio. To analyze this aspect, we provide in Table X the range of cost savings for nine different cases. Results obtained if the renewable generation comes from both wind and solar, only from wind or only from solar correspond to rows 2, 3 and 4, in that order. Results in column 2 are just a summary of those presented in Table IX. The results for the high-flex case (column 3) are obtained considering that $g1$–$g7$ are medium-load units, that is, their dispatch can be modified in real-time operation. Similarly, the results for the low-flex case (column 4) are attained if $g1$–$g7$ are assumed as base-load units, that is, their dispatch must be fixed 24 hours in advance. As expected, if the thermal generation portfolio is more inflexible, day-ahead dispatch and commitment decisions become more crucial to ensure an efficient real-time operation of the power system. For this reason, the proposed TA-UC achieves higher cost savings for the low-flex case.

To conclude this analysis, the proposed method has been tested on a higher dimension case study inspired by the Spanish power system. The thermal generation portfolio of Table XI includes 8 base-load units, 12 medium-load units, and 50 peak-load units. Some parameters have been slightly modified within a range to account for differences among units.
of the same type. The demand level and the capacity factor of wind and solar power generation correspond to year 2017 in Spain. The load shedding cost is €10,000/MWh.

Results in Table [XII] show that TA-UC outperforms CH-UC in the three analyzed cases, all with a renewable share of 50%. The highest cost saving amounts to 1.28% and is achieved if all renewable generation comes from solar power units. Notice also that for most days of the year, the proposed method yields cheaper operating decisions than the conventional one. The computational time to solve the day-ahead unit commitment problem for both approaches is lower than 10 seconds.

VII. CONCLUSIONS

The conventional unit commitment problem consisting of 24 hourly time periods relies on somewhat arbitrary and artificial division of time, which may lead to suboptimal and counterproductive dispatch and commitment decisions in the presence of intermittent renewable generation, thus resulting in a costly system operation. This paper proposes a novel time-adaptive unit commitment formulation, which also considers 24 time intervals but with different duration. The duration of the 24 time intervals depend on the net demand profile and is computed based on a chronological-time clustering technique.

As demonstrated by the numerical results, the proposed model leads to cost savings since it captures the intra-day variations of the net demand more precisely than the conventional approach. It also helps integrate more renewable generation than the conventional unit commitment model. The yearly cost savings amount to 0.2–2.6% for renewable penetration levels around 40–60%. Yearly cost savings are particularly significant in power systems with a high solar penetration level. Such technology creates abrupt and monotonic net demand variations around sunrise and sunset (the duck curve), which are more accurately accounted for by the proposed approach.

Finally, results also show that the lower the flexibility provided by the thermal generation, the higher the cost savings achieved by the proposed time-adaptive day-ahead unit commitment model.

Further research is required to investigate the performance of the proposed time-adaptive unit commitment if uncertainty in demand and renewable generation is considered. It would be also worth exploring the effect of network congestion on the results presented in this paper.

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