What time-period aggregation method works best for power system operation models with renewables and storage?

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***Abstract*—In this paper we compare two cutting-edge time-period aggregation methodologies for power system models that consider both renewables and storage technologies: the chronological time-period clustering; and, the enhanced representative period approach. Such methodologies are used in order to reduce the computational burden of highly complex optimization models while not compromising the quality of the results. With this paper, we identify which method works best, and under which conditions, in order to reproduce the outcomes of the hourly benchmark model.**

***Keywords*—power system models, clustering, time-period aggregation**

NOMENCLATURE

Indices

rp	Representative periods
k	Periods within a representative period
p, p'	General hourly periods
g	Generating unit
i	Nodes
l	Transmission lines
t	Thermal unit ($t = t(g)$)
s	Storage unit ($s = s(g)$)
g_i	Generator g connected to node i
li	Lines that end in node i
lo	Lines that start in node i
$h(p, rp, k)$	Relation between periods p and representative periods rp

Parameters

C^{ENS}	Energy non-served cost [M€/GWh]
E_s	Pumping Efficiency [p.u.]
P_g^+	Maximum output production [GW]
P_g^-	Minimum output production [GW]
RU_t	Ramp up limit [GW]
RD_t	Ramp down limit [GW]
C_t^{var}	Variable cost [M€/GWh]
C_t^{int}	Fixed cost [M€/h]
C_t^{st}	Start-up cost [M€]
$D_{rp,k,i}$	Hourly demand per node [GW]
$I_{rp,k,s}$	Inflows for hydro storage [GWh]
Q_s^+	Maximum consumption [GW]
R_s^+	Maximum reserve [GWh]
R_s^-	Minimum reserve [GWh]
T_l^+	Maximum power transfer per line [GW]
W_{rp}^{rp}	Weight of representative period[h]
W_k^k	Weight of subperiod [h]
M	Moving window for inter-period [h]

Variables

$u_{rp,k,t}$	Binary commitment decision
$y_{rp,k,t}$	Binary start-up decision
$z_{rp,k,t}$	Binary shut-down decision
$p_{rp,k,g}$	Production of the unit [GW]
$q_{rp,k,s}$	Consumption of the unit [GW]
$\hat{p}_{rp,k,t}$	Production above min [GW]
$pns_{rp,k,i}$	Power non-served [GW]
$pf_{rp,k,l}$	Power flow
$sp_{rp,k,s}$	Spillage [GWh]
$R_{rp,k,s}^{inter}$	Reserve at the end inter period [GWh]
$R_{rp,k,s}^{intra}$	Reserve at the end intra period [GWh]
$R0_s$	Initial reserve [GWh]

I. INTRODUCTION

The transition of the power system from its current state to the power system of the future is heavily influenced by the growing penetration of renewables combined with the increasing importance of storage technologies [1]. In order to design the optimal power system of the future and support decision making in the transition process, optimization models are employed. Mid- or long-term operation or generation expansion planning models often span a time horizon of several months, years or decades. An hourly representation of this time horizon usually renders models that are computationally intractable. Hence arises the need for time-period aggregation methods that in one way or another reduce the dimensionality of the temporal space within the optimization model in order to make it computationally tractable.

The two main methods used to reduce the temporal dimension of long-term models are: choosing representative periods (such as days, weeks, etc.); or grouping together original time periods in blocks (often hours), which in the literature have been referred to as time/load periods, time slices [2] or load-duration curve blocks, and which are frequently obtained using clustering methods. Let us now briefly discuss these two methods separately.

On the one hand, the main problem of load-period methods is that, in general, they do not capture the chronology of the original time series. That is, chronological information is usually lost in the clustering process. This poses a serious issue when having to properly formulate storage technologies within the model, as chronological information is necessary to capture storage behavior. This shortcoming of the load-period method could be remedied by the recent systems-states approach [3], which recovers some chronological information of load periods. However, so far the system-states approach has only addressed operational problems and not investment problems. Moreover, the computational burden of this method increases when having to consider fast-ramping storage technologies [4]. To overcome the loss of chronology, the authors of [5] have proposed a novel chronological time-period clustering (CTPC) method to obtain a load-period type model that decides generation expansion planning (GEP) taking into account both renewables and inter/intraday storage. The resulting model, however, does not account for binary operating decisions such as startup/shutdown or dispatch.

On the other hand, in the representative-periods approach one does retain the chronology - at least within the representative period itself - which allows for an appropriate formulation of intraday (intra-period) storage technologies. However, when it comes to interday (inter-period) storage such as hydro for example, the representative periods face the same problem of lack of chronological information. The work of [4] has overcome this issue by proposing the novel method of enhanced representative periods (ERP) which accounts for both types of storage by recovering chronological information via a transition matrix. In [4], the authors apply their methodology to a unit commitment (UC) type model which mainly focuses on operational details, and only considers investment in storage technologies (but not in renewables or thermal technologies).

The purpose of this paper is to compare the two cutting-edge methods in time-period aggregation, i.e., CTPC and ERP, and assess their performance on a set of carefully-chosen case studies (operation only; with and without binary UC-type decisions; etc.) with the objective to obtain a roadmap of what method works best under what circumstances. Both methods are compared against an hourly benchmark (BM) model. We assess CPU time, and resulting errors of operating decisions, as well as overall system cost. Moreover, we focus our analysis on the operation of both short- and long-term (or seasonal) storage technologies. In order to achieve this objective the existing tools available for both the CTPC and the ERP methods have to be extended.

The contribution of this paper is hence threefold:

- First, we extend the existing ERP model formulation of [4] to account for the proper inclusion of renewables and different network conditions.
- Second, we extend the existing CTPC approach [5] to include UC constraints.
- We carry out an exhaustive comparison between the two methods.

The rest of this paper is organized as follows. In section II, we formulate the UC model that serves as the basis to compare ERP and CTPC, while in section IIIwe include and discuss the results of that comparison for different case studies. Finally, section IV concludes the paper with some remarks.

II. Methodology

This section contains the UC model formulation used in this paper. Due to space limitations, we do not elaborate on the model formulation itself, as it is a standard UC model. Instead, here, we focus on how to interpret and calibrate specific model parameters and details, in order to obtain the hourly BM, and the two approximation models CTPC and ERP. The model formulation is general but, for convenience, we consider a time horizon of 8736 individual hours of operation (that is, 364 days, or 52 weeks).

Let us briefly discuss the indices relevant to time representation: index rp corresponds to a representative period and could be a day, a week, or even a year; index k represents the time steps within a representative period (hours for example). Let us also mention the following parameters: W_{rp}^{rp} is a weight for each rp and represents the number of actual periods represented by this particular one; W_k^k represents the weight of each subperiod k within a representative period. Subsequently, we outline how to choose these indices and parameters in order to get BM, CTPC and ERP, in that order.

The hourly BM model consists of equations (1) - (13). We only consider one representative period rp – in this context rp would be a representative year - so the cardinality of rp is one, and its corresponding weight W_{rp}^{rp} is also equal to one (as we only have one of these representative years), and 8736 hourly subperiods k, whose individual weight W_k^k is also one.

The CTPC model is formulated by equations (1) - (13). Again, we only consider one representative period rp with weight W_{rp}^{rp} also equal to one. However, the subperiods k considered within the representative year are no longer hourly. In particular, we have 168 subperiods k, each with a different weight W_k^k which represents the duration of this subperiod (or cluster). The sum over weights W_k^k yields 8736 hours. Note that these clusters, and their corresponding weight are obtained ex-ante according to the clustering procedure described in [5]. This clustering procedure also yields the corresponding values for parameters depending on index k (such as demand, for example).

The ERP model is given by equations (1) - (14). ERP has 7 representative periods – here representative days – each of which has 24 subperiods k of duration 1 hour. Hence, W_k^k is equal to one. However, the weight of each representative day, i.e., W_{rp}^{rp}, corresponds to the number of days (of the year) that are being represented by each rp. The sum over W_{rp}^{rp} is the number of total days considered (here 364). Weights W_{rp}^{rp}, as well as parameters depending on rp and k are the result of an ex-ante clustering procedure (e.g. k-means or k-medoids) as mentioned in [6].

We briefly discuss constraints (1) - (12) that are standard UC constraints. In the objective function (1), total system costs are minimized. The demand balance equation is given by (2). Constraints (3)-(5) define power production, (6) defines start-up and shut-down logic, (7) represents ramping constraints, and (8)-(12) account for variable definitions. Now, we want to discuss the storage technologies s and constraints (13) and (14) in a little more detail.

Constraint (13) corresponds to a typical storage level constraint or what we refer to as "intra-period" storage constraint: state of charge now is equal to what it was in the previous period, plus inflows, plus what is charged minus what is discharged, minus spillages. Both BM and CTPC only work with chronological periods, and hence only need this intra-period storage constraint to represent all types of storage technologies, e.g., long-term technologies such as hydro, and short-term storage technologies, such as battery energy storage systems (BESS). However, ERP consists of 7 different representative days that maintain chronology within the day, but that are not chronological among them, meaning that $rp1$ does not necessarily before $rp2$. Hence, ERP requires a slightly different representation of long- and short-term storage technologies. In particular, ERP has two different storage constraints, (13) and (14), that we explain subsequently.

In ERP, constraint (14) aims at establishing chronology among the 7 representative days. In particular, every M time steps (168h in this example), this constraint imposes: state of charge now is what it was one week ago, plus all the inflows that occurred during this week, plus all that has been charged minus discharged during this week minus spillages. This constraint is particularly useful to capture long-term storage such as hydro in ERP. In ERP, long-term storage such as hydro is only represented by (14), and not by short-term storage constraint (13). While variables, such as charge/discharge, production and consumption exist for each hour of the representative day, for hydro, the state of charge variables only exist every M hours.

In ERP, short-term storage technologies, such as BESS, are modeled using the intra-period storage constraint (13). We also impose a cyclic constraint within the day, i.e., it is assumed that the last hour of the representative day comes before the first one. For further detail regarding this model formulation, the reader is referred to [4].

$$\begin{aligned} min \sum_{rp,k,i} W_{rp}^{rp} \cdot W_k^k \cdot C^{ENS} \cdot pns_{rp,k,i} \\ + \sum_{rp,k,s} W_{rp}^{rp} \cdot W_k^k \cdot \frac{C^{ENS}}{2} \cdot sp_{rp,k,s} \\ + \sum_{rp,k,t} W_{rp}^{rp} \cdot W_k^k \cdot C_t^{st} \cdot y_{rp,k,t} \\ + \sum_{rp,k,t} W_{rp}^{rp} \cdot W_k^k \cdot C_t^{int} \cdot u_{rp,k,t} \\ + \sum_{rp,k,t} W_{rp}^{rp} \cdot W_k^k \cdot C_t^{var} \cdot p_{rp,k,t} \end{aligned} \tag{1}$$

$$\begin{aligned} \sum_{g \in gi} p_{rp,k,g} - \sum_{s \in gi} \frac{q_{rp,k,s}}{E_s} \\ + \sum_{l \in li} pf_{rp,k,l} - \sum_{l \in lo} pf_{rp,k,l} \\ + pns_{rp,k,i} = D_{rp,k,i} \end{aligned} \quad \forall\, rp,k,i \tag{2}$$

$$\hat{p}_{rp,k,t} \leq (P_t^+ - P_t^-) \cdot (u_{rp,k,t} - y_{rp,k,t}) \quad \forall\, rp,k,t \tag{3}$$

$$\hat{p}_{rp,k,t} \leq (P_t^+ - P_t^-) \cdot (u_{rp,k,t} - z_{rp,k+1,t}) \quad \forall\, rp,k,t \tag{4}$$

$$p_{rp,k,t} = u_{rp,k,t} \cdot P_t^- + \hat{p}_{rp,k,t} \quad \forall\, rp,k,t \tag{5}$$

$$u_{rp,k,t} - u_{rp,k-1,t} = y_{rp,k,t} - z_{rp,k,t} \quad \forall\, rp,k,t \tag{6}$$

$$-u_{rp,k-1,t} \cdot RD_t \leq \hat{p}_{rp,k,t} - \hat{p}_{rp,k-1,t} \leq u_{rp,k,t} \cdot RU_t \quad \forall\, rp,k,t \tag{7}$$

$$p_{rp,k,g} \leq P_g^+ \quad \forall\, rp,k,g \tag{8}$$

$$q_{rp,k,s} \leq Q_s^+, sp_{rp,k,s} \leq R_s^+ - R_s^- \quad \forall\, rp,k,s$$

$$R_s^- \leq R_{rp,k,s}^{intra} \leq R_s^+, R_s^- \leq R_{p,s}^{inter} \leq R_s^+ \quad \forall\, rp/p,k,s \tag{9}$$

$$-T_l^+ \leq pf_{rp,k,l} \leq T_l^+ \quad \forall\, rp,k,l \tag{10}$$

$$\begin{aligned} p_{rp,k,g}, q_{rp,k,g}, \hat{p}_{rp,k,g}, , pns_{rp,k,i} \\ R_{rp,k,s}^{intra}, R_{p,s}^{inter}, sp_{rp,k,s} \geq 0 \end{aligned} \quad \forall\, rp,k,g, rp,k,i,s \tag{11}$$

$$u_{rp,k,t}, y_{rp,k,t} \in \{0,1\} \quad \forall\, rp,k,t \tag{12}$$

$$\begin{aligned} R_{rp,k,s}^{intra} = R_{rp,k-1,s}^{intra} + R0_{k=1,s} \\ + W_k^k \cdot I_{rp,k,s} + W_k^k \cdot q_{rp,k,s} \\ - W_k^k \cdot p_{rp,k,s} - sp_{rp,k,s} \end{aligned} \quad \forall\, rp,k,s \tag{13}$$

$$\begin{aligned} R_{p,s}^{inter} = R_{p-M,s}^{inter} + R0_{p=M,s} \\ + \sum_{\substack{h(p',rp,k),\\ p-M<p'\leq p}} (I_{rp,k,s} \cdot W_k^k - p_{rp,k,s} \cdot W_k^k \\ + q_{rp,k,s} \cdot W_k^k - sp_{rp,k,s}) \end{aligned} \quad \forall s, p: p \bmod M \tag{14}$$

III. Case Studies

Given the data described in the following Section III.A, we next compare the approximation models CTPC and ERP to the hourly BM for a base case (Section III-B); a renewable sensitivity case (Section III-C); and a storage sensitivity case (Section III-D).

A. Base Case: Data

This section only contains a concise, brief description of the data used in the base case study, as both the full model data and results are available on "https://stexem.iit.comillas.edu/".

The base case consists of a stylized power system of Spain, in which we consider 8 different thermal generation technologies (nuclear, different types of coal, CCGTs, OCGTs and fuel oil plants), two different types of storage technologies (hydro and a BESS), and two different types of renewable generation technologies (wind and solar). Hydro storage has been modeled considering minimum, maximum and an initial level of reserve, and does not allow for pumping. The considered BESS, on the other hand, allows for both charging and discharging. Wind production represents around 25% of total system demand, and solar production amounts to 12% of total demand. Even though the model formulation itself is flexible to accommodate the modeling of the power network, in the base case we only consider one single node.

The time horizon that is covered in this case study corresponds to 8736 individual hours of operation (or 52 weeks), for which we have available hourly data of demand, wind and solar production and hydro inflows. The CTPC model approximates these 8736 hours by using 168 chronological clusters of consecutive hours. Correspondingly, the ERP uses 7 representative days of 24 hours each (i.e., also 168 time steps).

All of the case studies have been modeled in GAMS using Gurobi, and solved on an Intel® Core™ i7-3770 with 3.40 GHz and with 16 GB RAM. All model versions (hourly BM, CTPC, or ERP) are MIPs and have been solved to a tolerance of 0.1%.

B. *Base Case: Results*

In this section, we compare the BM, CTPC and ERP models under a MIP framework. General model statistics can be found in TABLE I. The way in which we have chosen the time representation (the amount of representative days or clusters) in both the CTPC and the ERP model is such that both models have the same granularity when it comes to representing time and the same number of binary variables, which constitutes around 2% of the BM binary variables. The CTPC model has slightly more continuous variables and constraints, however, the system matrix is less dense as indicated by the non-zero elements. We now analyze how this affects CPU time.

TABLE I. General model statistics for BM, CTPC and ERP

	BM	CTPC	ERP
No. vars.	633537	12262	12124
No. binary vars.	340704	6552	6552
No. equations	672673	12937	12873
Non-zero elements	2555455	49220	58954

We start with a general comparison of the resulting MIP model objective function value and corresponding CPU times given in TABLE II. When solving the MIP models to a 0.1% tolerance, the BM model took 6 hours to solve while the CTPC took only 14 minutes, and the ERP model less than 1 minute. This means that both approximations are two to three orders of magnitude faster (CTPC is 130 times faster, ERP 630 times) than BM. Both approximations yield an objective function value within 3% of the BM (CTPC with a -1.8 and ERP with a 2.8% relative error).

TABLE II. Objective function value and CPU time

	BM	CTPC	ERP
Obj. function [M€]	673.77	685.87	655.43
CPU time (s)	21605.11	842.48	47.10

TABLE III contains the total production in GWh by each technology given by the BM and the two approximations. Let us discuss the renewable production (wind and solar). Actually, the ERP renewable production yields maximum possible wind and solar production, i.e., there is no renewable "spillage". However, we can see in the BM model that a small fraction of renewables is, in fact, spilled. Since the ERP does not consider all individual hours of the year, it does miss these specific hours where the system cannot use nor store renewable energy. The CTPC model on the other hand captures that there exist spillages but overestimates them slightly.

Nuclear production is approximated with a relative error of less than 5% by both CTPC and ERP. CCGT production is also estimated with a small 4.6% error under CTPC, and a 0.2% error under ERP. It seems that thermal technologies that produce a large amount of energy in absolute terms are approximated well by both methods.

TABLE III. Total generation (GWh) per generating technology in BM, CTPC and ERP

	BM	CTPC	ERP
Nuclear	6586.38	6319.40	6740.70
FuelOilGas	0.00	0.00	0.00
BESS	376.21	142.52	336.74
Wind	7773.73	7734.73	7813.55
Solar	3907.78	3834.41	3921.87
Coal	329.68	99.38	74.38
CCGT	11314.56	11836.96	11331.04
OCGT	153.16	230.70	182.13
Hydro	1545.15	1545.15	1545.15

Coal and OCGT production, on the other hand, are not captured well, due to the fact that the overall total coal and OCGT production is relatively small. This means that there are only few hours in the year where coal or OCGT production is required to meet system demand. The CTPC predicts a need for coal production but does not estimate its magnitude correctly due to the lack of hourly granularity. As for OCGT production, the CTPC over-estimates its production by 50% and the ERP by 19%. Probably ERP over-estimates OCGT production to make up for missing coal production. As for the CTPC, it very likely over-estimates the OCGT production because it under-estimates the use of the BESS, which could replace the peaking unit. Let us now analyze the storage technologies in more detail.

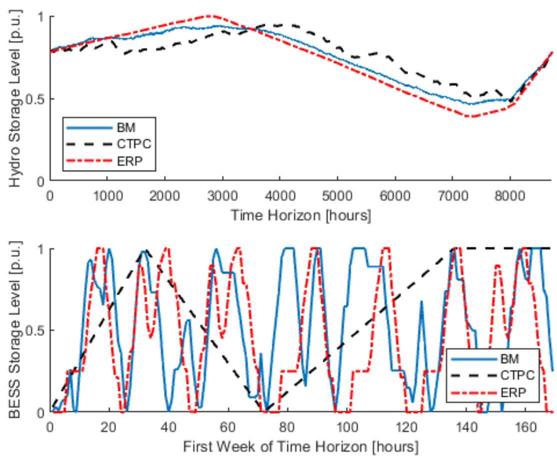

Fig. 1. *Storage level evolution over time of hydro (upper) and BESS (lower) in BM, CTPC and ERP models*

When analyzing storage results, we first mention that hydro production in GWh is approximated exactly by both models as can be seen TABLE III since a yearly cyclic storage level constraint has to be met in both models. Let us now focus on BESS production. While the ERP estimates BESS production with a 10.5% error, the CTPC does not capture this technology well with an error of over 60%. This result is to be expected due to the way in which both methods handle time reduction. The ERP maintains hourly detail within a day (and replicates these representative days through the year), while the CTPC clusters together consecutive hours. This means that under the CTPC approach it might happen that a time horizon of 24 individual hours is represented by only one cluster. Therefore, storage technologies whose discharge cycle is shorter (for BESS it is 4h) are not likely to be captured well by CTPC. Long-term dynamics, however, such as hydro storage are approximated better as can be seen in Fig. 1. In Section III-D we analyze the impact of the storage discharge length on our results.

In TABLE IV we present different error measures for both storage technologies (hydro and BESS). In particular, we assess the error between the annual hourly evolution of the BM model and the two approximations. To that purpose, we calculate the difference (allowing positive and negative deviations) of the BM storage level for each hour of the year and the corresponding hours of the CTPC and ERP approximations, and, in TABLE IV we present the average value of this error with the label "avg. error". We also report the same value but this time considering the absolute value of the difference in each hour with the label "avg. abs. error". Finally, we report the mean squared error (MSE).

TABLE IV. STORAGE (HYDRO AND BESS) LEVEL AND ERROR RESULTS IN CTPC AND ERP

	CTPC	ERP
Hydro avg. abs. error [p.u.]	0.0575	0.0387
Hydro avg. error [p.u.]	-0.0110	0.0177
Hydro MSE [p.u.^{2}]	0.0036	0.0020
BESS avg. abs. error [p.u.]	0.3767	0.2042
BESS avg. error [p.u.]	-0.0229	0.0533
BESS MSE [p.u.^{2}]	0.2220	0.0865

As can be observed in TABLE IV and Fig. 1, in terms of following the hourly evolution of hydro, ERP performs slightly better (see MSE), however, if we let positive and negative deviations cancel out, then CTPC performs slightly better in avg. error. For the BESS, ERP performs better than CTPC in MSE and avg. abs. error due to the short duration (i.e. 4h) of the discharge cycle, which gets washed out in the CTPC clusters (the shortest being 7h). However, in terms of avg. error CTPC and ERP is a little bit better. While CTPC might not be an adequate tool to approximate hourly evolution of storage levels, it performs very well in terms of average error.

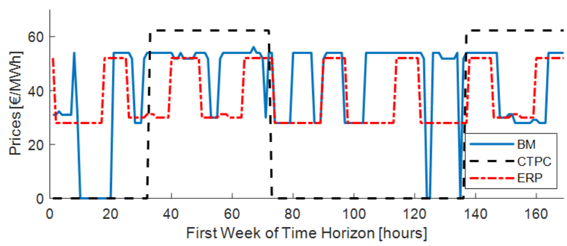

Fig. 2. *Hourly price results in models BM, CTPC and ERP*

Finally, we analyze hourly price results. In Fig. 2, we present the hourly evolution of price for the first week of the year. TABLE V contains the same error measures as used for storage, and we have also included annual average price. Since CTPC clusters together larger blocks of consecutive hours, we do not observe a typical daily load profile as indicated by a larger MSE than under the ERP method. However, in terms of avg. error and avg. annual price, CTPC is better than ERP. Even though CTPC does not replicate hourly profiles, on average, it performs well. ERP, on the other hand, does better in terms of emulating an hourly price profile as indicated by its MSE.

TABLE V. PRICE AND ERROR RESULTS IN MODELS BM, CTPC AND ERP

	BM	CTPC	ERP
Avg. annual price [€/MWh]	48.04	45.56	43.28
Avg. abs. error [€/MWh]	-	19.79	12.14
Avg. error [€/MWh]	-	2.47	4.76
MSE [(€/MWh)^2]	-	23108	22810

C. *Renewable Sensitivity Analysis*

In this section, we study the impact of the type of renewable technology involved in our power system generation mix on the quality of our approximation models. In the base case, we had a renewable mix of solar and wind, solar being 12% of total system demand, and wind 25%, each with its hourly profile. The total available renewable energy was 37%. We now run two sensitivity cases: a solar-only and a wind-only case. In each of the cases, the total available renewable energy amounts to 37%.

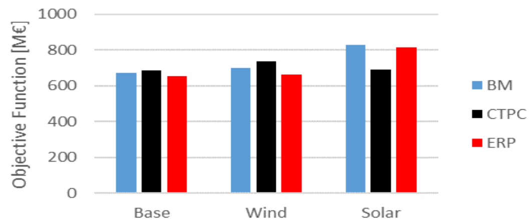

Fig. 3. *Objective function value in Base, all Wind, and all Solar cases in BM, CTPC and ERP*

In Fig. 3, we observe the different values of the objective function in each of the cases (Base case, all Wind case and all Solar case) for all the models. When the renewable source is all wind, the trend is similar to what we observed in the base case: CTPC slightly over-estimates the total system cost, and ERP slightly under-estimates it. In absolute terms, the relative error is similar in both approximations. The CTPC system is a bit more costly because it under-estimates BESS production (due to their short time dynamics) and over-estimates peaking production such as OCGT. ERP on the other hand, slightly over-estimates Nuclear and BESS production and underestimates OCGT. As mentioned previously, ERP is prone to thinking that the system is more flexible than it actually is because not all hours of the year are observed.

In the all solar case, CTPC does not approximate the total system costs adequately. There is a relative error of 17%, whereas ERP only yields a 2% error. This is due to the fact that solar has a very different production profile than wind. In particular, solar profiles are very much dependent on the hour of the day. CTPC clusters together large chronological blocks of hours and hence the shape of the solar profile and corresponding system requirements are washed out. Operating conditions are hence not replicated correctly, for example BESS production is grossly under-estimated (only 73 out of 500 GWh are predicted). This behavior is expected to change when considering longer storage cycle durations. Since ERP maintains an hourly profile in the intra-day storage constraint, operating conditions are mirrored more accurately.

We also compare the total renewable spillage in all different cases and observe that ERP handles the solar (20% error) technology better than wind (73% error). Since ERP maintains daily granularity, solar profiles adapt better to the way ERP handles the time horizon. Wind, on the other hand, does not exhibit repeating daily patterns and is hence more dependent on the actual moment in time when it occurred. With CTPC we observe the opposite. The temporal structure of CTPC adapts better to actual wind conditions over time, but daily patterns of solar are not captured that well.

D. BESS Cycle Duration Sensitivity Analysis

This section explores the effect of the charge/discharge duration of the BESS. In the base case, we have a maximum storage level of 800MWh and a 200MW maximum charge/discharge rate, which means that a full BESS could be discharged in 4 hours (or one full charge/discharge cycle of 8 hours). This is a relatively short time frame, which has an impact on the quality of BESS results of the CTPC model. Hence, we explore different cases of the BESS discharge/charge duration: 4 hours (base case), 8, 16 and 32 hours.

In the results, we observe that the ERP relative error in the objective function remains relatively constant no matter the discharge duration; CTPC errors, however, decrease with increasing BESS discharge duration. When BESS time dynamics become longer, and go away from the short-term daily cycle, the chronological CTPC time clusters adapt better and the approximation increases in quality.

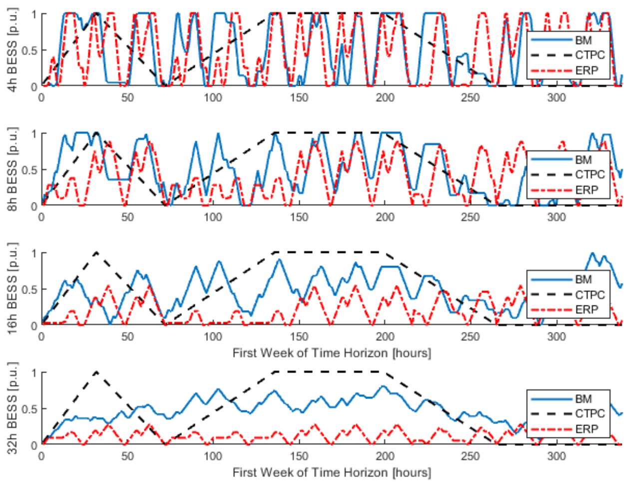

Fig. 4. *Storage Level Evolution of BESS with 4h, 8h, 16h and 32h discharge duration in BM, CTPC and ERP models*

In Fig. 4, we show the evolution of the BESS storage level in the first two weeks of operation. Note that it is a coincidence that CTPC operation is the same during the first weeks in all these figures. However, we want to observe ERP operation. When discharge duration increases, ERP fails to properly approximate the BM storage level. Since BESS is considered a short-term storage technology, it only has an intra-day storage constraint with a 24h cyclic constraint, and no inter-day storage constraint, which would allow capturing dynamics beyond one day. With a discharge duration of 32h, for example, we clearly see how the BM is increasing while the ERP has a zero storage level every 24 hours and hence, consistently under-evaluates the actual storage level.

IV. Conclusions

In this paper we have compared two approaches (CTPC and ERP) with different ways to simplify time representation in order to approximate an hourly unit commitment model. From the base case study, we conclude that ERP is more efficient in terms of CPU, better predicts short-term storage production such as BESS and yields a smaller regret in terms of UC decisions and hydro scheduling. CTPC, on the other hand, obtains a slightly better objective function value, and handles long-term dynamics, such as hydro storage, well. It also obtains a better estimate for average market prices.

In a sensitivity analysis we vary renewable production to all wind and all solar and observe that CTPC handles wind better than solar, because solar depends on a short-term daily profile which is washed out in the CTPC time representation. ERP on the other hand, predicts solar production better than wind production, because it has daily granularity, but lacks detailed representation of wind over time.

When increasing the discharge duration of the BESS, we observe that while CTPC objective function values improve, ERP errors stay the same, and storage level predictions deteriorate due to the lack of inter-day BESS constraints.

We conclude that while each methodology has its advantages and disadvantages depending on the interest of the study, combining both methodologies might be promising – a topic that we will explore in future research.

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