TOWARDS EXACT TEMPORAL AGGREGATION OF ENERGY SYSTEM MODELS WITH ENERGY STORAGE TIME-COUPLING CONSTRAINTS

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Motivation

Energy storage systems (ESS), such as battery storage and hydropower reservoirs, are widely acknowledged as critical assets for mitigating the uncertainty inherent to variable renewable energy (VRE) sources [1]. However, optimization models for joint scheduling of VRE and ESS resources over long horizons are inherently complex, due to intricate interactions among heterogeneous units and the temporal coupling constraints of ESS. This complexity motivates using aggregated models constructed via time series aggregation (TSA) to reduce computational burden. Still, the temporal coupling introduced by ESS remains a challenge for constructing aggregated models [2], as standard a priori TSA methods, such as k-means [4], k-medoids [5], or hierarchical [6] clustering, focus on capturing the statistical features of the input data, rather than aiming to accurately approximate the output solution of the resulting aggregated model.

To address the limitations of a priori TSA methods, the concept of a posteriori TSA methods has recently emerged, specifically aimed at minimizing errors in the aggregated model output. Nevertheless, existing a posteriori methods often rely on heuristics and typically lack formal performance guarantees. To overcome this, Wogrin [7] proposed an a posteriori TSA method that leverages the identification of active constraint sets in the optimization model to perform TSA while exactly preserving its optimal solution. Yet, this approach does not support optimization models with ESS time-coupling constraints and relies on ex-ante knowledge of the full-scale, non-aggregated model solution for TSA.

Methodology and Novel Contributions

The main contributions of this study are as follows: (1) We extend the theoretical results from [4] to models that support time coupling due to ESS, deriving a 4-step conceptual argument for the exact disaggregation into independent, parallelizable submodels and subsequent aggregation of periods within each submodel (see Figure 1) that achieves an exact aggregation of its full-scale counterpart. (2) Given that these theoretical conditions stem from ex-ante knowledge of the full-scale model solution, we propose a machine learning classifier to predict active constraint sets and inform TSA without relying on ex-ante knowledge of the optimal solution. (3) Since the active constraint sets are determined by the internal dynamics and technical characteristics of the VRE and ESS resources, we validate the classifier across different configurations, such as VRE paired with battery storage or hydropower reservoirs, and analyze their impact on aggregation and parallelization potential.

Numerical Examples and Validation

Using an illustrative optimization model for the joint scheduling of VRE and ESS resources over one year, we demonstrate that, under perfect information, the proposed approach achieves a 369-fold reduction in computational burden (lower bound) relative to the corresponding full-scale model, while incurring zero error in the objective function value and aggregated decision variables. We further validate the proposed classifier across a range of VRE and ESS configurations by benchmarking solution quality and computation time against full-scale models, showing its practical applicability under realistic settings where perfect information is not available.

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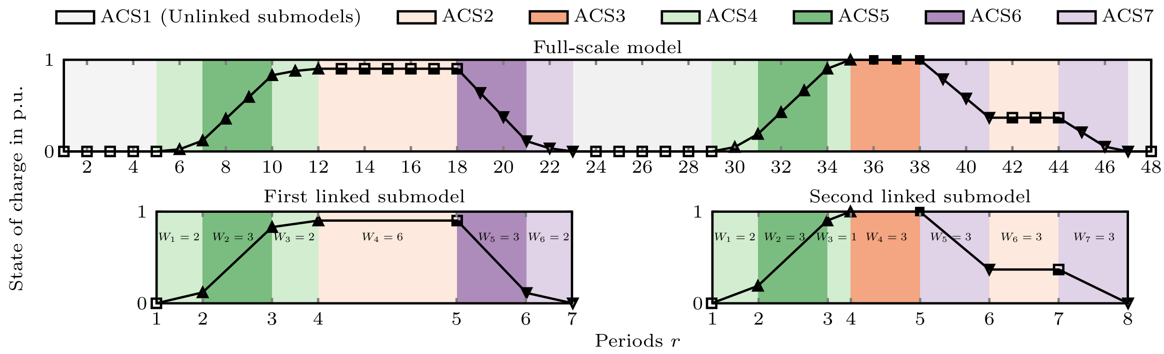

Figure 1: Disaggregation into submodels (top) and aggregation within submodels (bottom) via active constraint sets.

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