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Towards a hybrid approach for intra-daily recourse strategies

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Abstract

This paper highlights continued work on the question of combining Supervised Learning (SL) and Mixed Integer Programming (MIP) in order to solve intra-daily recourse strategies computation problems, in the field of energy management. Our goal is twofold. On the one hand we wish to share with the research community which are the hot open problems associated with the hybrid method developed in [3]. On the other hand, we highlight and analyze, and introduce solution methods for three key methodological bottlenecks related to the question of predicting which power units are the most important ones for these recourse strategies, in order to make the optimization process compatible with operational constraints.

1 Intra-daily recourse strategies in energy management

In the energy management domain, daily production plannings are based on forecasts of the power demand, regulatory constraints on the network and the initial state of the production facilities. Optimal plannings minimize the overall production cost while satisfying the demand. But along the day, unexpected events make the demand forecast inaccurate, rendering the initial plan inappropriate. Consequently, there is a strong need for methods that are able to compute intra-daily recourse strategies in order to reactively adapt the initial plan to the updated situation. Finding these recourse strategies is a difficult problem. Consider a modeling of the daily planning problem as an optimization problem P; then an intra-daily version M can be derived by adding new variables and constraints accounting for the regulatory requirements attached to the intra-daily modification process. On the French power network, these regulation rules specify that the electricity producer can only change its production plan every hour, at fixed times, and that a plan change (also called re-declaration) can imply the plan modification of at most 30 power units. Unfortunately, this harder problem needs to be solved in a very short span of time (a few minutes), for its solution to be implementable in practice. Hence, one is looking at a harder version of the original problem which needs to be solved in a shorter time.

2 Making the best of both worlds

A solution method for this problem of time-constrained optimization was proposed in [3][1]. It is built upon the idea that, although M is harder to solve than P, its resolution could be dramatically simplified if one was able to predict which 30 units are the ones participating in the optimal redeclaration. Based on this statement, solving M decomposes into two subproblems: first constructing a predictor whose purpose is the inference, given the data which specifies M, of the optimal value of a subset of boolean variables, and secondly solving a simplified version M' where the corresponding variables have been frozen to the predicted values. This way, the SL part tries to capture the general structure of the redeclaration process, while the Optimization part insures local optimality. We consider a historical set of problems $\{M_i\}_{i=1...N}$, written as MIP problems, that can be solved offline, without any constraint on the resolution time. These problems might have different numbers of constraints and different formulations but they all deal with the optimization of recourse strategies for the same power network (although some units might be down in some of the instances solved). From the optimal redeclarations obtained by offline resolution of these historical examples, one builds a boolean variable predictor mapping the variables describing the optimization problems to the vector of the 30 most likely units for an optimal redeclaration (Figure 1). When a new problem arises online, the boolean variable predictor is called to assign values to some of the discrete variables (corresponding to the participation of a unit to the redeclaration), in order to generate a simpler problem, whose resolution is much more likely to be compatible with the operational constraints.

3 Identifying bottlenecks

This paper aims at determining which are the current bottlenecks of the aforementioned approach (in order to put in perspective some of its strengths and weaknesses) and suggesting relevant ways of solving them.

[1] Another approach, similar in spirit, was proposed in [1]

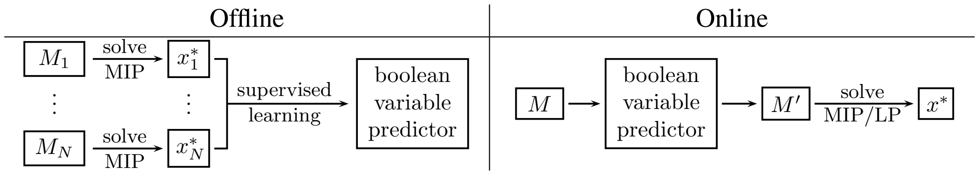

Figure 1: Construction of the boolean variable predictor and online MIP simplification

Unifying the description of M. While the MIP formulation of M always deals with the same network and, hence, the same decision variables, the number of constraints can vary. But the input variables of the SL method used to build the predictor are specifically the coefficients defining the MIP problem's constraints and objective function. Consequently, it is necessary to define a unified set of input variables allowing a common representation of the M problems. These variables need to be obtained from the raw data of M's coefficients, by exploiting energy experts knowledge to build good indicators. We also use iterative dimensionality reduction to cope with the very large number of coefficients (millions) in M.

Adapting the SL method. Previous attempts [3] at predicting optimal redeclarations were based on a method of Boosting [4] of decision trees and SVMs. While the method has not demerited on small instances, one can question its ability to scale to the very high-dimensional instances induced by the complete description of the real-life M-problem. Hence, adaptation of the SL method is one of the bottlenecks identified. An interesting option for dealing with these complex training instances lies in energy-based (sparse) models [2] which are known to adapt well to large-scale problems.

Predicting a sequence. A key feature of the prediction problem at hand is that one tries to predict a *sequence* of units participating in the redeclaration, within which the terms might be interdependent. In other terms, unit 4 might be crucial in the redeclaration only because it comes together with unit 3. The approach presented in [3] captured the likelihood of participation in redeclaration, but not the interdependency between the units redeclared. To overcome this difficulty and to predict a relevant sequence of 30 units, we consider the sequence prediction problem as a finite horizon sequential decision problem. In this problem, a first unit is selected at step 1, given the description of M; then a second unit is selected at step 2, given the first decision and M, and so on until the 30th. This way, every decision takes into account the whole sequence of previous decisions and hence captures the interdependency between units belonging to the optimal redeclaration. A direct corollary of this approach is that one does not build a single predictor anymore, but a sequence of 30 predictors, working in closed-loop in order to find the optimal 30-units sequence as illustrated in Figure 2.

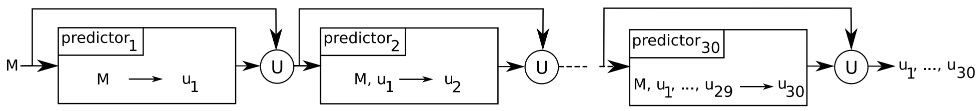

Figure 2: A sequence of closed-loop predictors

4 Conclusion

The contribution presented brings up three key bottlenecks in the process of taking the approach of [3] one step closer to real-world energy management applications. For each of them, we provide an explanation of its nature an new ideas and methods for overcoming it.

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